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# Development and Assessment of Signal Processing Algorithms for Assistive Hearing Devices

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## Abstract

Speech identification in the presence of background noise is difficult for children with auditory processing disorder and adults with sensorineural hearing loss. The listening difficulty arises from deficits in their temporal, spectral, binaural, and/ or cognitive processing. Given the lack of improvement with conventional assistive hearing devices, alternate speech processing methodologies, which exaggerate the temporal and spectral cues, need to be developed to improve speech intelligibility for individuals who have poor temporal and/ or spectral processing.

This thesis first, reports results from a series of experiments on subjective and objective assessments of two different schemes of envelope enhancement algorithms (dynamic and static) across different types and levels of background noise. The subjective results revealed that the speech intelligibility scores are lower for children with auditory processing disorder compared to children with normal hearing. The subjective results also demonstrated that enhancing the temporal envelope is much more beneficial for children with auditory processing disorder when compared to children with normal hearing. Comprehensive objective assessments, which were conducted by developing novel intrusive and non-intrusive objective speech intelligibility predictors, demonstrated that both dynamic and static envelope enhancement algorithms are only effective in improving speech intelligibility under certain processing conditions that depended on the type, level and location of the background noise. Furthermore, the application of noise reduction algorithms prior to the envelope enhancement techniques increased their range of effectiveness. Second, using the proposed objective predictors, the effectiveness of a companding architecture (which enhances both temporal and spectral cues) is shown to be better than temporal envelope enhancement alone, across different noisy environments in the presence of a noise reduction algorithm.

Third, the application of the binaural dichotic processing is evaluated in stationary and non-stationary background noise environments through subjective experiments. The subjective results demonstrated that the dichotic processing is mainly effective in improving speech intelligibility for stationary background noise at poor signal to noise ratios. It is also shown that the incorporation of a noise reduction algorithm as a front-end to the dichotic hearing processing is inferior to increase its range of effectiveness regardless of the type and level of the background noise.



**KEYWORDS**: Auditory processing disorder, Sensorineural hearing loss, Dynamic envelope enhancement, Static envelope enhancement, Dichotic hearing processing, Hearing aid speech perception index, Modulation spectrum area.

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# Nomenclature

| | |
|---|---|
| ADC | Analog to Digital Converter |
| ANSD | Auditory Neuropathy Spectrum Disorder |
| APD | Auditory Processing Disorder |
| BBBPF | Broad Band Band-pass Filters |
| CI | Cochlear Implants |
| CIL | Confidence Interval Levels |
| CPU | Central Processing Unit |
| CV | Consonant Vowel |
| DAC | Digital to Analog Converter |
| DBM | Deepen Band Modulation |
| DEEDT | Dynamic Envelope Enhancement Data Trained |
| DSP | Digital Signal Processing |
| DT | Decision Tree |
| ED | Envelope Detector |
| EE | Envelope Enhancement |
| ERB | Equivalent Rectangular Bandwidth |
| FFT | Fast Fourier Transform |
| GUI | Graphical User Interface |
| HA | Hearing Aid |
| HASPI | Hearing Aid Speech Perception Index |
| HI | Hearing Impaired |
| HINT | Hearing in Noise Test |
| HL | Hearing Level |
| I/O | Input / Output |

| | |
|---|---|
| IDE | Integrated Development Environment |
| IFFT | Inverse Fast Fourier Transform |
| iOS | Internet Operating System |
| IPP | Intel's Performance Primitive |
| JACK | Jack Audio Connection Kit |
| LSNR | Listener Signal to Noise Ratio |
| MHA | Master Hearing Aid |
| MHASPI | Modified Hearing Aid Speech Perception Index |
| MidSig | Middle Signal |
| ML | Maximum Likelihood |
| MMSE | Minimum Mean Square Error |
| ModA | Modulation Spectrum Area |
| MTBN | Multi Talker Babble Noise |
| NBBPF | Narrow Band Band-Pass Filters |
| NH | Normal Hearing |
| NHC | Normal Hearing Children |
| NR | Noise Reduction |
| PC | Personal Computer |
| RAM | Random Access Memory |
| RAUs | rationalized arcsine units |
| RM | Remote Microphone |
| RMS | Root Mean Square |
| RMSE | Root Mean Square Error |
| SEEDT | Static Envelope Enhancement Data Trained |
| SI | Speech Intelligibility |

| | |
|---|---|
| SNHL | Sensorineural Hearing Loss |
| SNR | Signal to Noise Ratio |
| SPL | Sound Pressure Level |
| SRTN | Speech Recognition Threshold in Noise |
| SSN | Speech Shaped Noise |
| SSNR | Source Signal to Noise Ratio |
| STFT | Short Time Fourier Transform |
| VCV | Vowel Consonant Vowel |
| WDRC | Wide Dynamic Range Compression |
| WModA | Weighted Modulation Spectrum Area |

# Chapter 1

# 1 Introduction

## 1.1 Overview

Hearing assessment typically involves the measurement of hearing sensitivity in different frequency regions resulting in an audiogram [1]. While the audiogram is the front-line measurement of hearing loss, it does not adequately describe the functioning of the impaired auditory system. In particular, it does not capture the auditory processing capabilities such as auditory discrimination, auditory pattern recognition, auditory performance in noisy and reverberant environments, and the performance in the presence of competing signals [2]. Usually, researchers in the auditory signal processing field are interested in developing algorithms that modify speech to provide benefits in specific situations, for example, to increase speech intelligibility in noisy background environments [3]. Speech intelligibility indicates the ability of an individual to comprehend a speech signal and is a useful measure of auditory processing capabilities of hearing impaired listeners. Speech intelligibility can be assessed at the sentence, word or phoneme level, and is typically evaluated using subjective experiments. However, subjective measurements are costly and time consuming processes as they require individuals to participate in an experiment [4]. This thesis examines alternative signal processing algorithms that aim to enhance temporal, spectral and/or binaural features, and their performance in the presence of different types and levels of background noise is evaluated through subjective and objective speech intelligibility measurements.

In this chapter, human hearing and different types of hearing disorders are introduced, as well as brief overview of conventional hearing aids and cochlear implants. Development platforms for implementing signal processing algorithms for assistive hearing devices are introduced next. After that, the problem statement, which highlights the limitations of the conventional hearing aid technologies, are discussed followed by an alternative class of signal processing algorithms. Finally, the objectives and the outline of the thesis are presented.

## 1.2 Introduction and background

### 1.2.1 Human hearing

The sense of hearing involves the perception of sound through our auditory system. The human auditory system consists of the outer, middle, and inner ear as well as the central auditory nervous system. The basic anatomy of the human ear is illustrated in Figure 1-1 [5]. As can be seen from Figure 1-1, the outer ear consists of the pinna and the external auditory canal, which leads to the tympanic membrane. The middle ear consists of the tympanic membrane and three middle ear bones, the malleus, incus and stapes classified as ossicles. The inner ear deals with neural processing, and has three parts, the semicircular canals, the vestibule and the cochlea. The cochlea is the organ where vibrations are converted to electrical signals that are processed by the central auditory nervous system [6].

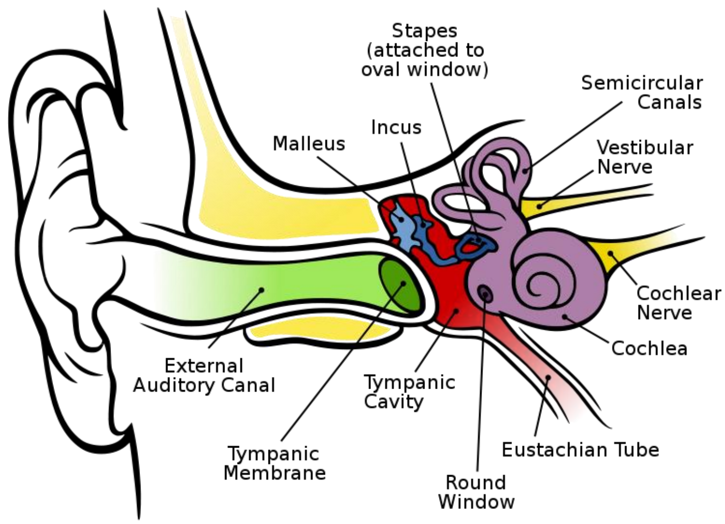



**Figure 1-1: Anatomy of the human ear** [6]

### 1.2.2 Hearing disorders

Over the last 20 years, the proportion of people suffering from hearing loss has been increasing steadily [1]. In general, hearing loss can be divided into two categories: conductive and sensorineural. Conductive hearing loss is a disorder caused by a problem with the conduction of pressure vibrations from the outer ear to the cochlea. Problems with this type of hearing disorder can occur at several places such as blocking the ear canal or fluid building up in the middle ear which can disrupt the normal mechanisms of the ossicles [6]. Conductive hearing loss is improved by performing surgery to remove fluids or applying bone anchored hearing aids that can allow sound to be conducted through the bone instead of the middle ear [1].

Sensorineural hearing loss (SNHL) is a disorder that reduces hearing sensitivity when the sensory or neural cells or their connections within the cochlea are absent or not functioning well. This type of hearing loss is caused by noise exposure, ototoxic drugs, and aging. Hearing aids with nonlinear compression feature can provide benefits for patients with sensorineural hearing loss, especially for those who have loudness recruitment[1].

Within the broader category of sensorineural hearing loss lies the Auditory Processing Disorder (APD). Individuals with APD may have deficits in temporal, spectral, or binaural processing [7]. In general, individuals with APD have disruptions in their auditory nerve and central auditory pathways that significantly degrade their auditory processing capabilities [8]. It is estimated that about 3-5 % of children suffer from APD, which directly impacts their ability to learn from what is heard and to communicate with others [9]. Auditory processing deficits are also prevalent in adults, particularly in adults over 60 [9].

In addition, the Auditory Neuropathy Spectrum Disorder (ANSD) can be considered as a subset of the broader APD category. People suffering from ANSD may have near-normal cochlear function, but not well-functioning auditory nerves. This type of hearing disorder affects the timing of neural activity in the auditory pathway and disrupts temporal aspects of auditory perception. ANSD can result from damage to the inner hair cells, or the synapse between the inner hair cells and/or the auditory nerve [10],[11]. However, the exact causes and treatment methods are not well understood. It is estimated that ANSD patients constitute approximately 10% of the hearing impaired population [12].

Temporal processing which consists of modulation thresholds, gap detection , and frequency discrimination are areas of significant impairment for individuals with ANSD [10]. The poor speech identification in individuals with ANSD is mainly due to reduced ability to follow the envelope (amplitude modulations) of the speech signal. Conventional hearing aids do not enhance the temporal envelope of the signal to compensate for temporal processing deficits in individuals with ANSD. In addition, conventional hearing aids reduce the amplitude fluctuations when a nonlinear amplitude compression feature is used, and this may result in the deterioration of performance in hearing sensitivity for people who have ANSD [10]. Hence, when designing assistive hearing devices to increase speech intelligibility for these patients, techniques to bring the temporal and spectral characteristics of speech within their thresholds should be given the priority.

### 1.2.3 Conventional hearing aid technology

Figure 1-2 illustrates processing stages of a high-end hearing aid. At the beginning, the acoustic signal is captured by microphones, then the microphone signals are processed into a single signal with the directional microphone unit [13]. The resulting mono-signal is further processed separately in different frequency ranges. Generally, it requires an analysis filterbank and the corresponding signal synthesis filterbank. The main frequency-dependent processing steps are noise reduction and signal amplification combined with the dynamic compression processing blocks. These processing blocks as well as the directional microphone unit are discussed briefly in the following subsections.

#### 1.2.3.1 Amplitude compression

The major role of compression technology is to reduce the dynamic range of signals in the environment so that all signals of interest can fit within the restricted dynamic range of a hearing-impaired person. This means that intense sounds must be amplified less than weak sounds. A compression technology uses a compressor, which is an algorithm that automatically reduces its gain as the signal level somewhere within the hearing aid rises. It should be mentioned that this type of technology is beneficial for patients who are suffering from sensorineural hearing loss as they have restricted dynamic range of hearing [1].

#### 1.2.3.2 Directional microphone technology

This technology is effective when there is spatial separation of a signal of interest (speech), and unwanted signal (noise). A typical directional processing system in current generation hearing aids is constructed either with two ports on a single microphone or with multiple independent microphones, whose outputs are appropriately delayed or mixed electronically. This procedure reduces sound originating from behind the hearing aid wearer while amplifying sounds coming from the front [1]. The major disadvantage of this technology is that it is ineffective when desired and undesired sounds are spatially collocated.

#### 1.2.3.3 Noise reduction algorithm

Adaptive noise reduction technology aims to reduce the amplification of noise compared to speech. This can be achieved by determining the noise segments which are significantly intense compared to speech and applying less amplification to these segments. In hearing aids that apply this technology, speech is detected, followed by estimations of the speech and noise levels at some point in time and across frequency to determine the appropriate gain reduction for each frequency region [1]. There are several techniques to perform adaptive noise reduction. However, most systems use either Wiener filtering or spectral subtraction [1]. These two techniques can decrease the gain in each frequency region where the Signal to Noise Ratio (SNR) is deteriorated. It should be noted that these types of techniques can enhance the overall SNR, but they cannot modify the SNR in any narrow frequency band. Furthermore, since background noise can change its characteristics within a short period of time, both Wiener filter and spectral subtraction do not register any information about new noise and are trying to remove a noise that is no longer present. Hence, these techniques are most suitable for stationary noises such as machinery and air conditioning noise.

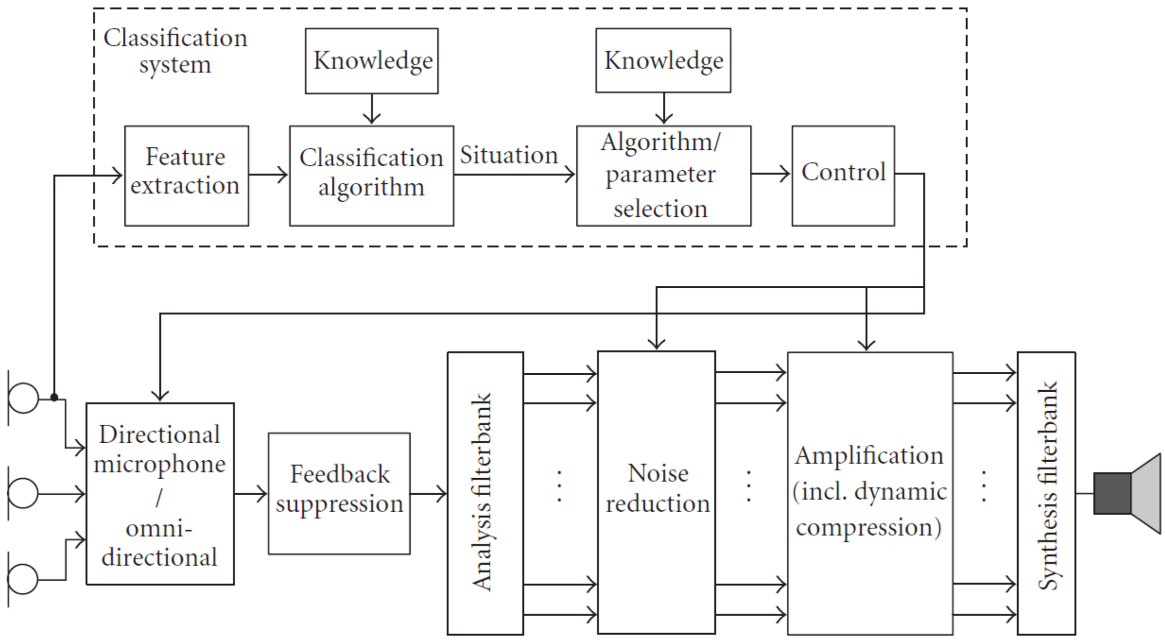



**Figure 1-2: Processing stages of a high-end hearing aid** [13]

## 1.3 Cochlear implants

Cochlear implants (CIs) are devices that bypass the inner ear and provide direct electrical stimulation to the auditory nerve. They involve a surgical implantation of an array of electrodes into the cochlea; hence, they are invasive and expensive. Cochlear implantation is routinely performed on patients with sensorineural losses where the cochlea is the primary section of dysfunction [14].

CIs for individuals with ANSD is a debatable issue. If the site of the dysfunction is the cochlea, then bypassing the inner hair cells with direct stimulation of the vestibulocochlear nerve should provide a good benefit in terms of the speech perception. However, if the pathological condition lies in the nerve itself, the CI might not be beneficial in improving the speech perception in patients with ANSD.

Despite the potential benefits of CIs, drawbacks also exist. These drawbacks include high cost, standard surgical risks, cochlear damage resulting from insertion of the electrode array (thus destroying residual hearing) [15] and no guarantee of oral speech communication skills development [14].

Furthermore, there is a considerable variability in the outcomes of children with ANSD receiving cochlear implants [16]. Some studies have shown considerable speech perception improvement with cochlear implantation, while others have shown no improvement. Therefore, as concluded in [16], hearing aid trials should be given to all the cases diagnosed with ANSD and those who received intermediate benefit from hearing aids should be considered for CIs.

## 1.4 Development platforms

Research and development in the field of speech and audio signal processing consists of three development stages: offline development, real-time development, and system integration for the fully developed algorithm [3]. In general, a new signal processing algorithm is firstly developed for offline processing, which consists of the evaluation of the algorithm performance by using an offline development database (e.g. speech database). For real-time development, the algorithm is evaluated by considering real-time issues (e.g. short time latency) before implementing on an embedded system. Finally, the algorithm is integrated and realized as a prototype [3]. It is pertinent to point out that in most cases, only the first two stages of algorithm development is conducted in academic institutions [3].

Both offline and real-time processing require specific development platforms. The platform design should specify the hardware and software as well as the rules that describe how these two should fit together. In existing offline development platforms, high-level programming languages such as MATLAB, Simulink, and C/C++ are used on a personal computer (PC) platform [3]. It should be noted that by considering today's computing power, any complex signal processing algorithm can be easily developed for offline processing. On the other hand, the real-time development platforms are much more complex compared to offline development platforms. The existing real-time platforms typically consist of at least signal input/output (I/O) devices, analog-to-digital converter (ADC), central processing unit (CPU), random-access-memory (RAM), and a digital-to-analog-converter (DAC). Furthermore, the real-time platforms need a faster processor and an operating system conducive for real-time processing. In the next chapter of the thesis, a literature review of the existing platforms for offline and online processing will be examined and discussed.

## 1.5 Problem statement

Although several research works have been proposed toward assistive hearing devices to improve communication for the affected people, today's commercial hearing aids have some restrictions in providing benefits for hearing impaired listeners. For example, Wide Dynamic Range Compression

(WDRC) algorithm, which is available in today's commercial hearing aids, can deteriorate the speech intelligibility of an individual with SNHL in noisy environments [17]. Furthermore, individuals with SNHL, who have a dead zone in a high-frequency range, cannot hear the sound components in the dead zone region at any gain values of the WDRC [17]. In addition, conventional hearing aids and assistive listening devices offer little benefit to listeners with auditory processing deficits. For example, Mathai and Appu [18] investigated the effect of four different hearing aid settings on speech perception of seventeen adults with late onset ANSD. Results showed no significant differences between unaided and aided performance, indicating the lack of benefit from conventional amplification. Walker et al. [19] compared the speech perception capabilities of children with ANSD and children with SNHL, and found that the ANSD children demonstrated inferior speech recognition in a noisy environment even with the provision of a hearing aid. In a similar vein, Kuk [20] reported data on hearing aid benefits collected from 14 children diagnosed with APD, which showed that some but not all participants demonstrated improved performance with hearing aids. Researchers have also investigated the effectiveness of remote microphone (RM) assistive listening devices for APD and ANSD populations ([21] and [22]). A recent systematic review by Reynolds et al. [23] found moderate benefits from RM systems for children with APD, although the practicality of using an RM in a number of ecologically valid situations has been questioned by Kuk [20]. Therefore, alternative signal processing strategies for APD/ANSD and SNHL individuals need to be developed and validated.

## 1.6 Thesis objectives

This thesis addresses the abovementioned problem through the development of alternative signal processing algorithms and comprehensively evaluating their performance across a variety of environmental conditions. Three classes of algorithms were investigated: envelope enhancement, companding, and dichotic processing.

Envelope enhancement (EE) algorithms, which attempt to mitigate temporal modulation processing deficiencies by enhancing the temporal peaks and valleys of a speech signal, form the initial foci of this thesis, as evidence exists that such a strategy can indeed be effective for individuals with ANSD and SNHL [24], [10], [25], [26], and [27]. The first objective is to evaluate the performance of two different schemes of EE algorithms subjectively with children with APD at sentence-level speech perception. For this purpose, Hearing in Noise Test (HINT) database [28] was used as a clean speech, where sets of phonetically balanced sentences are presented at different processing conditions. The speech intelligibility in noise is measured using custom software developed in our laboratory.

The second objective is to benchmark the effectiveness of the EE algorithms across a number of noisy conditions. However, subjective testing of the EE algorithms at different types and levels of background noise can become an onerous task. Therefore, objective instrumental measures that employ computational models to predict the speech quality and intelligibility are attractive [4], [29], [30], [31]. A good objective metric that correlates well with subjective data can be used as a surrogate for benchmarking the performance of signal processing algorithms and allows for a more comprehensive assessment of the signal processing algorithms across a number of noise types and levels. It should be noted that in this thesis, the comprehensive assessments of the EE algorithms are conducted by developing new intrusive and non-intrusive objective instrumental predictors of speech intelligibility. Furthermore, the application of noise reduction algorithms prior to the EE algorithms is investigated at different levels and types of background noise in terms of speech intelligibility.

The third objective is to benchmark the performance of companding algorithms. Companding algorithms enhance both the spectral and temporal contrast in such a way that the compression is prevented from degrading spectral contrast in regions close to a strong spectral peak while allowing the benefits of improved audibility in regions distant from the spectral peaks [32], [33], and [34]. Previous research demonstrated that hearing aids incorporating a companding strategy, which enhances spectral and temporal contrast, may be beneficial to individuals with ANSD [34]. In this thesis, the proposed objective intelligibility predictors are used to comprehensively evaluate the performance of companding algorithm in different noisy environments, in the presence and absence of a noise reduction algorithm.

Finally, there is evidence that dichotic signal processing algorithm, which uses a pair of comb filters with complementary pass bands and stop bands, can reduce the spectral masking thresholds in individuals with SNHL and improve frequency selectivity of this group of hearing impaired listeners [35], [36], [37], [38] and [17]. The rationale behind dichotic processing is that the spectral components that are likely to mask or get masked by each other are presented to opposite ears. Hence, the spectral masking may be reduced [38]. Thus, the fourth objective is to implement a new binaural dichotic processing scheme and investigate its speech intelligibility performance with individuals with SNHL across different types and levels of background noise. Furthermore, the effectiveness of incorporating a noise reduction algorithm as a front-end to the application of binaural dichotic processing is evaluated across different processing conditions.

## 1.7 Thesis outline

The thesis is organized as follows. In Chapter 2, current envelope enhancement, companding and binaural dichotic processing algorithms are described as well as the published evidence. In addition, two objective metrics of speech intelligibility are examined and presented. Then, a literature review of portable platforms for hearing aid applications is presented, followed by a description of the open Master Hearing Aid (openMHA) portable platform. Finally, a single-channel-noise reduction plugin of the openMHA platform and the log Minimum-Mean-Square-Error (logMMSE) noise reduction (NR), are described and explained.

In Chapter 3, the development of the dynamic EE algorithm for RM applications is described. In addition, the subjective data collection procedure for children with suspected APD is described, and the results are analyzed for statistical significance. Furthermore, an optimal objective speech intelligibility metric is derived to predict the perceptual impact of the dynamic EE algorithm followed by the objective assessment of the dynamic EE in the presence of different types and levels of background noise. Finally, the effectiveness of incorporating noise reduction algorithms (viz. logMMSE and MHA) as a front-end to the dynamic EE is discussed.

In Chapter 4, the performance of the static EE for hearing aid applications will be evaluated subjectively for children with APD, followed by a statistical analysis of the subjective scores. In addition, the optimal objective predictor will be derived in a manner like Chapter 3, which is utilized to predict the subjective scores across different levels of non-stationary background noise experiment, followed by the effectiveness of the application of (logMMSE and MHA) noise reductions as a front-end to the static EE.

In Chapter 5, the robustness of the individual objective predictors, which are derived in Chapter 3 and 4, is investigated followed by the derivation of a generalized intrusive and non-intrusive objective models. Then, the effectiveness of companding architecture is evaluated by utilizing the non-intrusive generalized objective predictor, followed by the effectiveness of incorporating a NR algorithm (MHA) as a front-end to the companding architecture.

In Chapter 6, the performance of dichotic processing is investigated subjectively with hearing impaired (HI) listeners with SNHL. Furthermore, the effectiveness of the same binaural dichotic processing algorithm is evaluated by incorporating an additional noise reduction algorithm (MHA) as a front-end to the application of dichotic processing.

Chapter 7 summarizes the findings of this thesis, highlights the contributions, and provides recommendations for future work, which consists of techniques and suggestions for practical real-time implementation of these signal processing algorithms as signal processing plugins of openMHA portable platform as well as proposing methods for customizing the algorithm parameters.

# Chapter 2

# 2 Literature Review

This chapter discusses various speech enhancement algorithms including the dynamic EE, deepen band modulation (DBM) technique, companding architecture, and binaural dichotic processing as well as their application to improve speech recognition in people with ANSD and SNHL. Furthermore, a literature review of existing portable platforms for hearing aid applications is presented, followed by an introduction of the openMHA portable platform. Finally, two objective metric indices of speech intelligibility are examined followed by the description of the logMMSE and MHA NR algorithms.

## 2.1 Envelope enhancement algorithm

Most of the work completed in the field of ANSD speech enhancement has been related to EE [10], [24], and [25]. These studies have shown an increase in word identification scores when the envelope of the speech was enhanced, prior to the contamination by background noise.

### 2.1.1 Principles

As mentioned in the previous chapter, studies indicate that there are three major psychoacoustic impairments that likely contribute the most to degraded speech perception in people with ANSD: temporal modulation thresholds, gap detection thresholds and frequency discrimination. The primary focus of the EE concentrates on compensating for the poor modulation detection thresholds by reinforcing temporal speech cues. Slow temporal envelope modulations in the 4-10 Hz range have been shown to provide useful cues for speech perception [4]. Hence, enhancing the speech envelope over these slow modulation rates can exaggerate the useful cues. An example of an envelope-enhanced signal is shown in Figure 2-1.

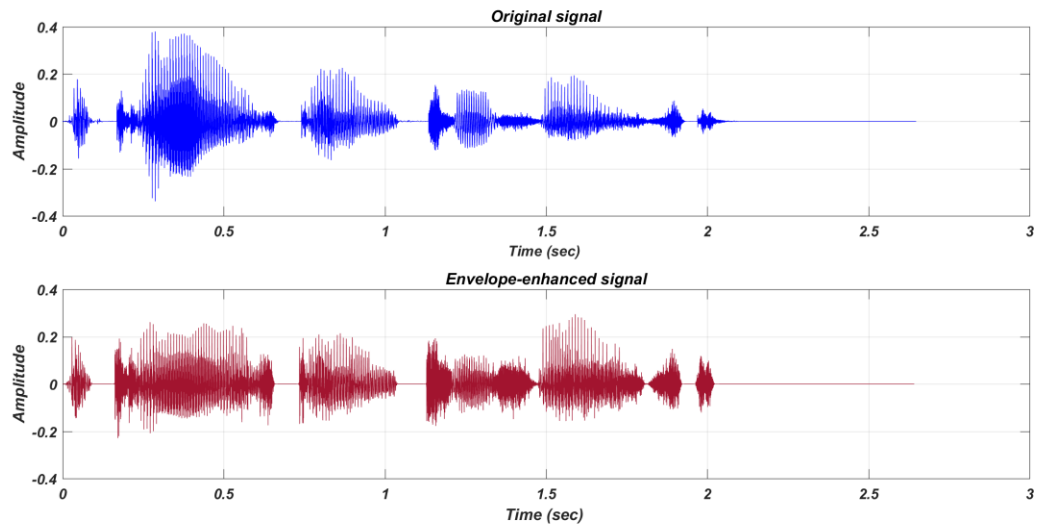



**Figure 2-1: Comparison of speech signals with and without EE for the speech sample, "The car is going too fast".**

The procedure used to expand the speech envelope is described in greater detail in Chapter 3. It is pertinent to point out that in this thesis, the EE technique that was adopted from Narne et al. [25] is termed as 'dynamic EE', as the amount of envelope enhancement is not fixed and varies with respect to the minimum and instantaneous values of the envelope amplitude.

### 2.1.2 Published results

The performance of the dynamic EE algorithm was evaluated with ANSD subjects by Narne and Vanaja in [10], [24], and [25] (for various conditions), and the results from these studies are discussed next in detail.

The effect of envelope enhancement on speech perception in individuals with auditory neuropathy was investigated in [24]. More specifically, the objectives were to investigate the ability of individuals with ANSD to identify consonant-vowel (CV) stimuli for different modulation enhancement bandwidths. In other words, an ideal cut-off frequency for temporal envelope extraction (and thus enhancement) was being sought after. Eight people with ANSD were tested. The results showed that speech identification improved with envelope enhancement. Furthermore, the greatest improvement was found for an enhancement bandwidth of 3-30 Hz.

Perception of envelope-enhanced speech in the presence of noise by individuals with auditory neuropathy was investigated in [25]. Considering people with ANSD have particularly poor speech discrimination in noise, the motivations for this study were clear. Fifteen people with ANSD were tested and significant improvements due to envelope enhancement were found in quiet and +10 dB SNR for all subjects. Four subjects with a less severe case of ANSD, improvements were also significant at +5 and 0 dB SNR.

The perception of speech with envelope enhancement in individuals with ANSD and simulated loss of temporal modulation processing was studied in [10]. Results from two experiments were reported in [10]. In Experiment I, an ANSD simulator was used to test the effectiveness of the envelope enhancement on 12 normal hearing listeners. The parameters of the ANSD simulator were adjusted to simulate mild, moderate, severe and profound degrees of neuropathy. The test stimuli consisted of bi-syllabic words in Kannada (a language spoken in a southern state of India). Speech scores were calculated by counting the number of words correctly repeated and converting to a percentage of total words presented. Results revealed a significant main effect of degree of ANSD and a significant interaction between the degree of ANSD and stimuli (processed vs. unprocessed) and a significant difference between mean identification scores across all degrees of simulation.

In the second experiment, 12 people with ANSD and 12 normal hearing listeners were recruited to compare the results of envelope-enhanced speech to unprocessed speech. Word recognition scores were obtained using the same test stimuli from Experiment I. Statistical analysis of the recognition data showed a significant improvement in speech scores for envelope-enhanced stimuli with ANSD subjects, but no significant differences were found with normal hearing subjects.

### 2.1.3 Significance to Thesis

EE has been shown to benefit speech identification for people with ANSD. However, previous studies only explored the assessment of EE algorithms after application to short segments of speech (consonants, vowels, and words). In addition, a comprehensive assessment of the impact of background noise on the performance of EE is lacking. To elaborate on this further, consider Figure 2-2 which represents a typical RM setup where the RM is placed close to the source and the listener is wearing the hearing aid, which is connected wirelessly to the RM. Depending on where the EE algorithm is implemented (either in the RM or the hearing aid), background noise can add to the desired signal before and after the EE algorithm and can potentially create a differential impact. In previous studies, the background noise was only added after the speech signal is enhanced and ready to be transferred to a listener. In addition to the noise location, the impact of different noise types (stationary vs. non-stationary) has not been previously investigated. Finally, all the previous research work only considered the subjective evaluation of the EE algorithm. However, as mentioned in the previous chapter, benchmarking the EE algorithm across a variety noisy conditions can become a costly and time-consuming procedure. Therefore, to make further contribution to the field in this research area, this thesis applies EE to sentence-level speech perception tasks and objectively benchmarks the EE algorithm across different types and levels of the background noise. A good objective metric that correlates well with subjective data is proposed as a surrogate for benchmarking EE algorithm performance across a number of noise types and SNRs. To the best of our knowledge, this thesis is the first study conducted to show that the benefit of EE in children with suspected APD for RM applications.

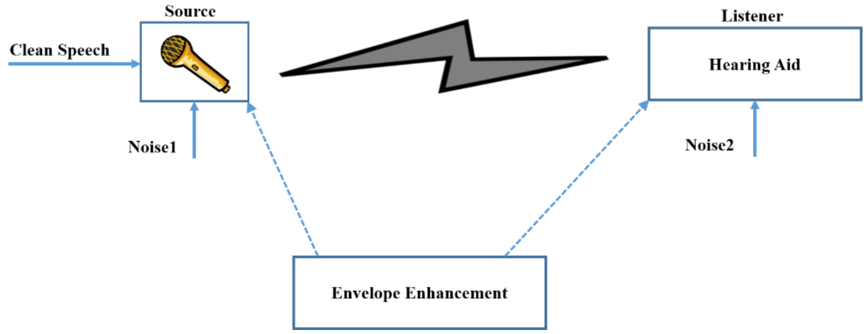



**Figure 2-2: Block diagram of a typical assistive listening device setup incorporating the EE strategy.**

## 2.2 Deepen Band Modulation (DBM)

The second EE strategy is the DBM technique. The effects of temporal envelope enhancement using the DBM technique on speech perception in quiet and in the presence of background noise were evaluated with individuals with ANSD and SNHL with promising results in [26] and [27].

### 2.2.1 Principles

DBM technique is another technique of envelope enhancement, which was recently evaluated by Shetty and Kooknoor [27] using an algorithm adopted from Nagarajan et al. [39]. This EE methodology was applied to speech stimuli using the "Deepen band modulation" feature in the Praat software (version 6.0.25, Institute of Phonetic Science, University of Amsterdam, Netherlands). In this thesis, this EE technique is labeled as 'static EE' since it applies a fixed modulation boost over a restricted acoustic frequency range. An example of deepen band modulation signal is shown in Figure 2-3.

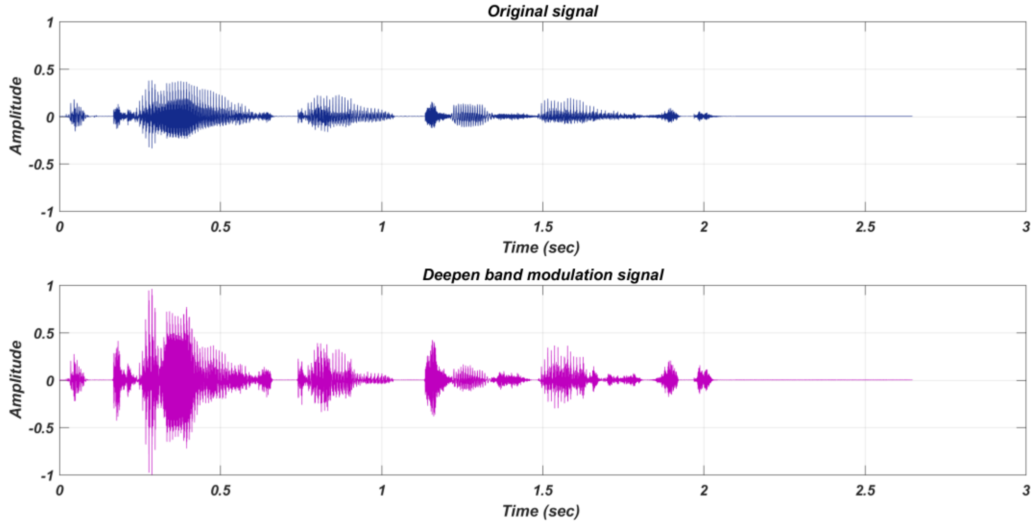



**Figure 2-3: Comparison of speech signals with and without DBM technique for the speech sample, "The car is going too fast".**

### 2.2.2 Published results

The effect of DBM technique on speech identification was evaluated in four groups of 10 people, young and old normal hearing, young and old hearing impaired listeners with mild to moderate SNHL in [26]. The results of this study generally showed that consonant identification scores in DBM conditions were significantly higher compared to unprocessed conditions, in both quiet and at 5 dB and 10 dB SNRs with multi-talker babble as the background noise, regardless of participant groups. In addition, the statistical analysis of their results revealed that younger adults achieved better consonant identification scores compared to older adults in both normal hearing and hearing-impaired participant groups irrespective of the processing condition and SNRs.

The goal of the research study conducted in [27] was to investigate the effect of DBM on phrase perception in quiet and stationary noise upon individuals with ANSD and SNHL. Twenty normal hearing listeners, 20 hearing impaired listeners with moderate SNHL, and 20 hearing impaired listeners with ANSD participated in the study. Four lists of phrases were used that each list comprised 10 phrases. Phrase recognition scores were evaluated in quiet and in the presence of stationary background noise at -1, -3, and -5 dB SNRs. These experimental results in general revealed that in each participants' group, the phrase perception score was better in DBM condition compared to unprocessed condition regardless of the SNR value. Furthermore, the statistical analysis of their results showed that phrase perception scores in quiet processing condition were not statistically different between DBM and unprocessed condition irrespective of the participant groups. However, the DBM phrase perception scores were statistically better compared to unprocessed condition at SNRs of -1 dB, -3 dB, and -5 dB for both SNHL and ANSD hearing impaired listeners.

### 2.2.3 Significance to Thesis

DBM technique has been shown to benefit speech perception for people with ANSD and SNHL. However, to date it has only been evaluated at phrase level and not sentence level for ANSD and SNHL subjects. In addition, in previous studies, the background noise was only added after the speech signal is enhanced and ready to be transferred to a listener. In this thesis, the DBM technique (static EE) is implemented in MATLAB for hearing aid applications, and its impact on speech intelligibility by children with APD is evaluated. Figure 2-4 represents a block diagram of the EE implementation for a typical hearing aid application, where the microphone of the hearing aid can pick up both speech and noise. In such a system, a NR block is potentially beneficial to separate speech from noise before enhancing the envelope of the speech signal, due to the fact that noise can reduce the modulation depth and create spurious modulations to the speech signal. In addition, the impact of applying different noise reduction algorithms as a front-end to the EE algorithm has not been previously investigated. Finally, a good objective metric that correlates well with subjective data is proposed as a surrogate for benchmarking static EE technique performance across a number of noise types and SNRs.  To the best of our knowledge, this thesis is the first study conducted to show that there is a benefit of DBM technique to children with APD for hearing aid applications, as shown in Chapter 4.

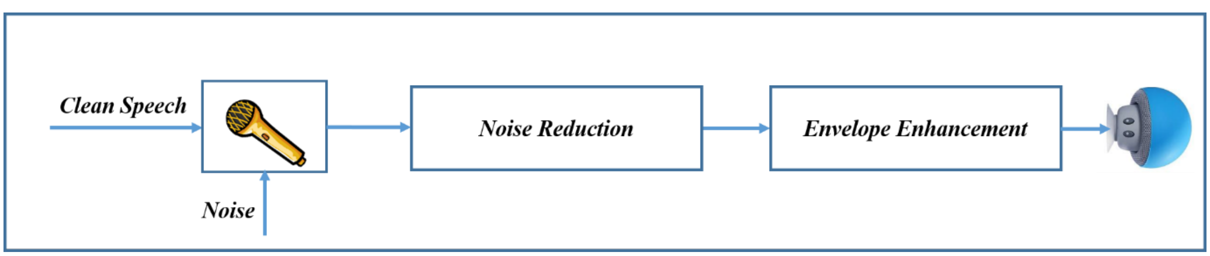



**Figure 2-4: Block diagram for implementing of EE in hearing aid application.**

## 2.3 Companding architecture

Poor frequency discrimination at lower frequencies (< 2000 Hz) is a common characteristic of people with ANSD [40]. Companding is a process that emphasizes the spectral peaks and valleys (as opposed to emphasizing the temporal peaks and valleys in EE) to aid with frequency discrimination. A research study conducted by Narne et al. [34] has evaluated the benefit of companding algorithm with ANSD subjects.

### 2.3.1 Principles

Turicchia and Sarpeshkar [32] proposed a companding architecture, which combines two-tone suppression – a non-linear phenomenon arising from complex interaction between outer hair cells of the inner ear and the basilar membrane – and dynamic gain control in order to increase the spectral contrast. By conducting such a strategy, a weak tone at one frequency is strongly amplified in such a way that is concurrently audible with a weakly amplified strong tone at another frequency. Hence, the asymmetric amplification due to compression degrades the spectral contrast, but when two-tone suppression strategies, which enhance contrast, are also simultaneously present, the compression is prevented from degrading spectral contrast in regions close to a strong spectral peak, while allowing the benefits of improved audibility in regions distant from the spectral peak [32]. Figure 2-5 compares the long-term averaged spectra of clean and companded speech signals. It can be seen from Figure 2-5 that companding does sharpen the spectral peaks.

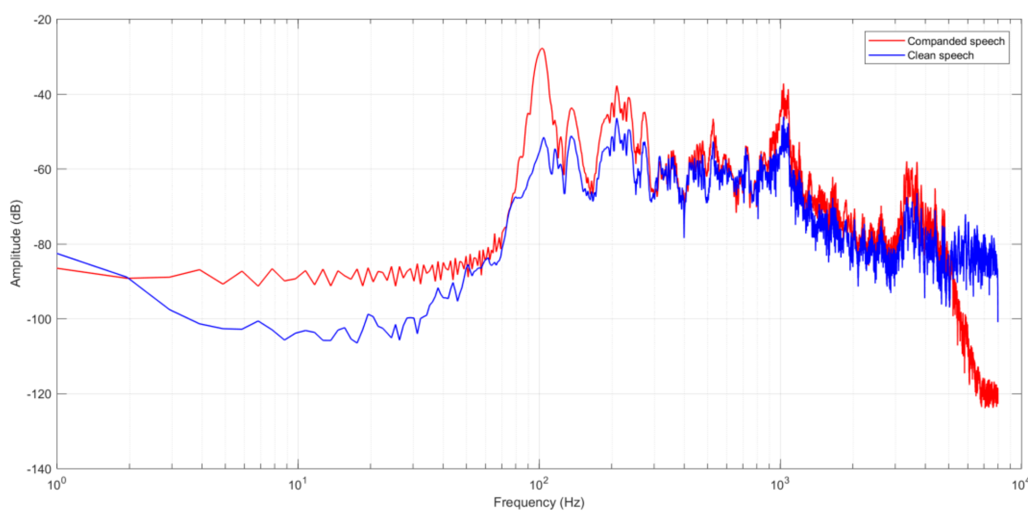



**Figure 2-5: Effect of companding on the spectral peaks of the speech sample, "The car is going too fast".**

## 2.3.2 Published results

Bhattacharya & Zeng [41] have examined the advantage of companding as a front-end noise suppression technique in listeners with cochlear implants. Both normal-hearing (NH) listeners and CI users performed phoneme and sentence recognition tests in quiet and steady-state speech-shaped noise. They observed that CI users showed significant improvements in both phoneme and sentence perception in noise. In general, their experimental results reveled that companding improved speech perception scores by 10 – 20 % in steady-state background noise. Recently, the effect of companding on speech perception in quiet and stationary background noise at different SNRs for individuals with ANSD and normal hearing was evaluated [34]. Speech perception was evaluated in two different experiments. In the first experiment, speech recognition threshold in Noise (SRTN) was evaluated at the sentence level in background noise at different SNRs ranging from 20 dB to -10 dB. The results from their first experiment revealed that mean difference in SRTN between original and companded stimuli was significantly different in both participant groups. In addition, the difference in SRTN between companded and original stimuli was more for ANSD subject compared to normal hearing subjects.

In their second experiment, consonant identification scores in quiet and at different SNRs, 15, 10, 5, and 0 dB were investigated. Their experimental results from the second experiment showed that companding showed marginal improvement only at 0 dB SNR in NH listeners. Listeners with ANSD showed a significant reduction in consonant identification scores in noise compared to NH listeners. In addition, none of the listeners with ANSD could identify any consonant at 0 dB SNR. Furthermore, listeners with ANSD showed significant improvements in consonant identification in quiet and 15 dB SNR with companding compared to the original stimuli.

## 2.3.3 Significance to Thesis

Companding technique has been shown to benefit speech perception for people with ANSD. However, to date it has only been evaluated subjectively with ANSD subjects in the presence of stationary background noise for hearing aid applications (viz. the background noise is added before companding). Hence, this thesis investigates the companding technique in the following steps. First, the companding algorithm is developed on the iPad platform for non-real time processing. This development platform allows a clinician to quickly change the algorithm parameters to compensate the patient deficit in frequency selectivity task procedure. Second, the performance of the companding is evaluated by applying an optimal objective index. Third, as previous research has shown that the effectiveness of the companding algorithm reduces in the presence of background noise [34], in this thesis, the effectiveness of a NR algorithm is evaluated as a front-end to companding algorithm for different types and levels of background noise. The objective evaluation of the companding algorithm for hearing aid application will be examined in Chapter 5.

## 2.4 Dichotic processing

Dichotic hearing may improve the frequency selectivity of individuals with HI. The bandwidths of the auditory filters of HI individuals are generally wider than those of NH persons, which is referred to as spectral smearing [42]. Hence, the frequency selectivity of HI individuals is relatively low. Binaural dichotic processing reduces the spectral masking threshold and improve the frequency selectivity of HI individuals. However, the clinical benefits of dichotic hearing on speech intelligibility are currently debated as dichotic processing improved speech recognition in some studies [38] and [42] , but other studies [43] and [44] showed that dichotic hearing did not improve speech recognition.

### 2.4.1 Principles

For dichotic processing, the input speech signal is processed by a pair of comb filters with fixed bandwidth or critical bandwidth for spectral splitting of the input speech signal. Then, the output signal of the odd filters is added together, and this summed signal is heard in the left ear. Furthermore, the output signals of the even filters were added together, and this summed signal is heard in the right ear at the same time. Figure 2-6 shows the block diagram of dichotic processing, wherein the input signal is processed by a complementary pair of comb filters. As mentioned before, splitting the speech into two complementary parts on the basis of frequency and presenting it binaurally may increase its intelligibility due to the fact that the spectral masking effect is reduced [42].

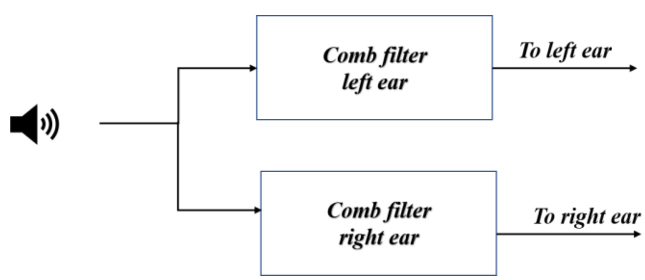



**Figure 2-6: Spectral splitting for binaural dichotic processing.**

### 2.4.2 Published results

Research study conducted by Chaudhari and Pandey [42] investigated the effectiveness of binaural dichotic processing on speech perception for vowel-consonant-vowel (VCV) and consonant-vowel (CV) words with HI participants. They utilized an 18 channel filterbank to split the speech signal into odd and even bands. Results associated with their study showed that employing dichotic signal processing improved recognition scores and reduced the response time for both VCV and CV words.

Murase et al. [43] reported that when they played recordings of VCV and CV syllables to four HI subjects in four different combinations (*viz.* diotic, diotic with amplitude -6 dB, dichotic with cross-over frequency 0.8 kHz, and dichotic with cross-over frequency 1.6 kHz), and the ranking of speech recognition performance scores was dichotic (0.8 kHz) > diotic > diotic (-6 dB) > dichotic (1.6 kHz).

Mani et al. [45] reported that when they conducted sentence recognition experiments with eight bilateral nucleus-24 implant users in three different processing conditions ( diotic, low-high dichotic, and odd-even dichotic), the ranking of speech recognition performance was diotic > odd-even dichotic>low-high dichotic.

Kolte and Chaudhari [44] reported that when they conducted a recording of VCV words processed by an 18-band dichotic comb filter to seven HI subjects, the speech perception score increased for four subjects, but decreased for three subjects. Furthermore, the response time decreased for five subjects but, increased for two subjects.

Kulkarni and Pandey [38] reported that when they played a recording of VCV words processed by an 18-band dichotic comb filters based on fixed and auditory bandwidth achieved improvement in consonant recognition and source direction identification. Furthermore, the improvement was significantly more for comb filters with auditory bandwidth when compared to ones with fixed bandwidth.

Hwang et al. [17], reported that the simultaneous application of nonlinear frequency compression and dichotic hearing on CVC recognition showed almost the same performance compared to the sole application of nonlinear frequency compression in a severe hearing loss simulation setting environment.

More recently, the research study conducted by Ozmeral et al. [46] investigated the impact of dichotic listening with NH participants and individuals with mild-to-moderate SNHL on VCV recognition test in the presence of asynchronous masker. The results associated with their study demonstrated that all participant groups achieved higher VCV recognition scores from dichotic presentation compared to diotic processing. However, the beneficial of dichotic signal processing was much less for HI compared to NH participants.

### 2.4.3 Significance to thesis

Dichotic processing has been shown to benefit speech perception for people with SNHL. However, to date it has only been evaluated with a restricted set of algorithm parameters, stimuli, and processing conditions as discussed in the following paragraph.

Some studies ( e.g. [38]) evaluated the performance of dichotic processing with SNHL patients only in quiet environments. The studies that had the background noise present, it was only added after the speech signal was processed dichotically, and limited types of background noise (e.g. white/pink noise) were considered. Hence, to make novel contributions to the field in this research area, this thesis evaluated an efficient implementation of the dichotic processing algorithm by using analysis and synthesis gammatone filterbanks in MATLAB. The algorithm is evaluated subjectively with HI listeners with SNHL in the presence of different levels and types of background noise (viz. stationary versus non-stationary) for binaural hearing aid applications, where the background noise is added before dichotic processing. In addition, the incorporation of a NR algorithm as a front-end to dichotic processing is investigated. The subjective assessment and evaluation of the dichotic processing algorithm for hearing aid applications is detailed in Chapter 6.

## 2.5 Portable platforms

Literature review indicates that portable hearing aid platforms could either be PC-based Digital Signal Processing (DSP) platforms or Smartphones. The former one can process high amount of audio data, whereas the later one is more portable, but harder to program and configure. However, in most cases, users can not modify the algorithm parameters during the use of the device. In the following, a summary of some of the more recent development platforms are examined.

Magotra [47] and [48] developed a portable digital hearing aid platform which consists of a laboratory-based PC system with a TMS320C30 DSP card and a wearable unit based on the TMS320C3X DSP chip. The proposed platform is a binaural hearing aid with two input microphone signals that can be sampled up to 32 kHz per channel and driving a stereo headphone at the output. Various algorithms such as frequency shaping, noise suppression, multi-band amplitude compression, and frequency dependent interaural time delay were programmed in the platform and tested on hearing impaired subjects in the real world as well as in the laboratory.

Researchers in [49] developed a high performance platform based on the Motorola DSP56309 signal processor. The device consists of a high quality external stereo ADCs and DACs with 20-bit word length. The user can only adjust the input/output gains by using controlled potentiometers. The algorithm parameters can be adjusted by a developed software suite that is accessed from an external PC. The authors indicated that such a platform can be helpful to evaluate new advanced hearing aid algorithms. The authors developed a more sophisticated system later on that worked based on a newer fixed-point DSP Motorola DSP56002. The new DSP platform was considered as embedded in a complete stand-alone system [50].

Authors in [51] developed a PC based platform for audio processing. The goal of the research work was to separate hardware and algorithm programming issues to allow the designer to develop algorithms without dealing with the hardware issues. The platform worked on a commercial PC (Pentium IV, 1800MHz) to implement an acoustic echo control unit that has two inputs and two output channels. The platform sampling rates were designed to be between 8 to 32 kHz range.

The research reported in [52] aimed to compare a smartphone-based hearing aid application with commercial hearing aids based on the traditional hearing aid algorithms that were discussed earlier in this thesis. Objective testing revealed similar electroacoustic results between smartphone-based applications housed on the iPod and the traditional hearing aids. In addition, most of the smartphone-based applications provided the opportunity to the user to adjust volume, frequency-gain response or both.

The authors in [53] developed a portable, user friendly, and flexible platform called the MHA platform. The platform employed a netbook computer with a custom audio interface to facilitate portability and flexibility. The platform offers a low-cost alternative to implementing hearing aid algorithms directly on hearing aids by replacing the digital hearing aid with a standard off-the-shelf PC. The platform provides an opportunity for evaluating complex hearing aid algorithms as it provides greater computational power. In addition, the platform allows modification of the algorithm parameters easily without the need for hardware modification. A dynamic range of over 90 dB for two and six input channel setups was reported. Recently, the same research group evaluated a high-performance platform in combination with the MHA framework to implement more processing algorithms such as binaural processing algorithms. The proposed platform allows researchers to run the MHA software framework on the integrated dual core ARM processor. New algorithms can be implemented as software/hardware plugins in the MHA software framework. In addition, the proposed platform can support up to eight audio input channels to support multichannel audio processing which consists of high quality external stereo ADCs and DACs with 24-bit word length and a sample rate of from 8 to 96 kHz [54].

### 2.5.1 Significance to thesis

#### 2.5.1.1 iPad platform

It should be noted that the dynamic EE and companding architecture were implemented as iOS applications for an iPad platform. The Xcode development system was utilized as the Integrated Development Environment (IDE), which was found to be a highly productive environment for building applications for Mac, iPhone, and iPad [55]. In addition, Swift was used as the programming language to develop application for iOS due to its versatility and intuitiveness. Furthermore, the VDSP portion of the Accelerate Framework was used to implement the required digital signal processing functions (e.g. vector and matrix arithmetic, Fourier transform, convolution and correlation, and filtering) [55]. It is important to note that this phase of development was motivated for non-real-time applications, and also because our Centre, the National Centre for Audiology, has developed software to conduct the psychoacoustic tests (*viz.* temporal modulation, gap detection, and frequency discrimination) on the iPad platform. Accessibility to the algorithms through the psychoacoustic test system will allow a clinician to quickly gauge their effectiveness, in case of abnormal psychoacoustic test results.

#### 2.5.1.2 Hortech open MHA

In February 2017, HorTech and Oldenburg University published the openMHA on GitHub under an open-source license (AGPL3) [56]. OpenMHA is a development and evaluation software platform that can execute hearing aid signal processing in real-time on standard computing hardware with a low latency between input and output sound [56]. As illustrated in Figure 2-7 , the openMHA consists of the following major components as discussed below [56].

1) The openMHA command line application (MHA)

It acts as a plugin host, which can load signal processing plugins as well as audio input-output modules (IO).

2) Signal processing plugins

It provides the audio signal processing capabilities and audio signal handling. In general, one openMHA plugin implements one specific algorithm. A complete virtual hearing aid signal processing can be achieved by a combination of several open MHA plugins.

3) Audio input-output modules (IO)

It can provide the proper interface for different applications of the openMHA. For real-time signal processing, the openMHA MHAIOJack module is used, which provides an interface to the Jack Audio Connection Kit (JACK). For offline processing, the module MHAIOFile provides audio file access.

4) The openMHA toolbox library (libopenmha)

It provides an easy-to-use mechanism to integrate real-time safe runtime configuration updates into every plugin.

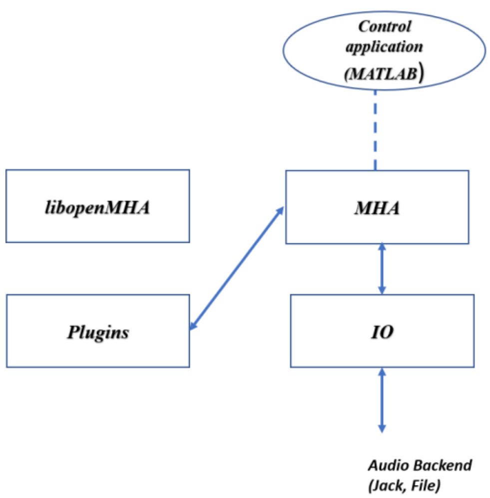



**Figure 2-7: Layered structure of the open Master Hearing Aid** [56]**.**

It should be noted that in addition to the iPad implementation of the dynamic EE, this algorithm is also implemented as a new plugin for the openMHA platform by implementing a C++ class derived from a generic base class, implementing the methods and compiling it to a shared object [56]. It is also pertinent to point out that the computational complexity of the developed dynamic EE is addressed by using Intel's Performance Primitive library (IPP) [57].

## 2.6 Objective metrics

Various computer-based objective measurement methods have been proposed to estimate speech intelligibility in the presence/absence of a background noise [30], [4], [29], and [31]. Generally, objective measurement methods can be divided [4] into two categories, intrusive or non-intrusive. The intrusive ones perform measurement in comparison to a reference speech signal, whereas the non-intrusive ones perform measurement independent of the reference speech signal. This thesis employs two objective metrics, *viz.* HASPI and ModA, to predict the speech intelligibility scores, as they have been shown to correlate well with subjective data [58], [31]. In the following paragraph, these two metrics are briefly described.

### 2.6.1 Hearing Aid Speech Perception Index (HASPI)

The feasibility of HASPI metric in predicting perceptual impact of speech in commercial hearing aids is recently evaluated by Kates et al. [58], which revealed that HASPI, has capability of measuring the differences that appear across different devices and processing settings. HASPI is an example of an intrusive metric and predicts speech intelligibility by utilizing an auditory model [30]. The auditory model consists of the middle ear transfer function, auditory filterbank, outer hair cell dynamic range compression, two tone suppression, and the temporal firing rate mechanism of the inner hair cells. The inputs to the auditory model are clean speech (reference speech) and processed speech (degraded speech). It should be noted that the model for the processed signal is adjusted based on the peripheral hearing loss. Generally, the auditory model compares the clean (reference speech), and the processed (degraded speech) inputs in terms of the temporal envelope and fine structure, and computes the envelope cepstral correlation, and three-level for fine structure covariance between the reference and processed speech signal. In the next stage, these raw features of HASPI (e.g. cepstral correlation and three-level fine structure covariances) are transformed into an estimated intelligibility score between 0 and 1, where 0 and 1 imply poor and excellent intelligibility respectively. Equation 2.1, shown below, illustrates the HASPI computational equation:

$$p = -9.047 + 14.817 * C + 0.0 * a_{Low} + 0.0 * a_{Mid} + 4.616 * a_{High} \tag{2.1}$$

$$H = \frac{1}{1 + e^{-p}}$$

where H is the estimated intelligibility score, C represents the cepstral correlation, and $a_{Low}$, $a_{Mid}$, and $a_{High}$ are the three-level fine structure covariances [30].

### 2.6.2 Modulation spectrum area (ModA)

The ModA [31] objective metric is an example of non-intrusive metric. First, the processed signal is limited (i.e., normalized) within a fixed amplitude level (i.e., [-0.8 0.8]). After that, the normalized input signal is decomposed into N = 4 bands spanning the signal from 300-7600 Hz. The frequency splitting is implemented by a series of fourth-order Butterworth filters. Then, the temporal envelope of each band is computed using the Hilbert transform, followed by down sampling to the rate of ($2\times f_{cut}$), and $f_{cut} = 10$ Hz. Hence, limiting the envelope modulation rate to $f_{cut} = 10$ Hz. For the next stage, the mean-removed envelope is passed through bandpass filters with center frequencies from 0.5-8 Hz. After that, the mean-removed root-mean-square (RMS) output of each bandpass filter is computed to generate the modulation spectrum within each acoustic frequency band. Then, the modulation indices, which cover the 0.5- 10 Hz modulation rate, are summed up to compute the area $A_i$ under the modulation spectrum of each frequency band. Finally, as shown in Equation 2.2, the $A_i$ values are averaged across all acoustic frequency bands to compute the average modulation-spectrum area (ModA). It should be mentioned that in the Equation 2.2, the ModA denotes the average modulation area across all acoustic frequencies for N = 4 as th number of acoustic bands. The rationale behind ModA is that as more noise is added to the signal, the modulation spectrum of the noise-masked envelopes becomes flat and shift downs (across all modulation frequencies) relative to the modulation spectrum of the clean envelope. As a result, the area under the modulation spectrum is reduced as the SNR decreases.

$$\mathrm{ModA} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{A_i} \qquad (2.2)$$

## 2.7 Noise reduction (NR)

Generally, NR algorithms can be categorized into four broad groups; spectral subtractive algorithms, Wiener filtering algorithms, statistical model-based algorithms, and subspace algorithms [59]. However, investigating and/or comparing the performance of all available NR techniques is out of scope and not considered as an objective for the present study. Hence, in this thesis, the performance of the well-known NR algorithm, *viz.* the logMMSE, and a single-channel NR plugin of openMHA, termed as “MHANR” are investigated as a front-end to the application of alternative signal processing algorithms. The reason to choose logMMSE and MHANR algorithms is because both of these NR techniques generate fewer artifacts (“musical noise”), that are typically associated with available NR techniques ([59] and [60]). In the following paragraph, the logMMSE and MHA NR techniques are introduced briefly.

### 2.7.1 logMMSE NR

The logMMSE algorithm belongs to the statistical-model-based noise reduction techniques and an example of algorithms based on maximum likelihood estimation. The algorithm estimates the log magnitude spectra by minimizing the mean square-error [61].

#### 2.7.1.1 Maximum likelihood estimation

Assuming that the input signal y(n) is the sum of a speech signal s(n) and an uncorrelated additive noise signal u(n), where n is the sample index. In the short-time Fourier transform (STFT) domain, the speech signal and noise are defined as S (K, L) and U (K, L) respectively, where K and L are the frequency and frame index respectively. Hence, the noisy speech, Y (K, L) is given by Y (K, L) = S (K, L) + U (K, L). *A priori* Signal-to-Noise-Ratio (SNR), $\xi$, is defined as the ratio of the speech power, $\lambda_s(K) = E\{|S(K)|^2\}$, and the noise power, $\lambda_u(K) = E\{|U(K)|^2\}$. A maximum likelihood (ML) estimate, $\xi^{ml}(K, L)$, of the *a priori* SNR given *a posteriori* SNR $\gamma(K, L) = \frac{|Y(K,L)|^2}{\lambda_u(K)}$, can be computed as shown in Equation 2.3.

$$\xi^{ml}(K, L) = \gamma(K, L) - 1 \qquad (2.3)$$

It can be noted that any deviation of the noise power from its expected value, $\lambda_u(K)$, results in fluctuations in the ML SNR estimate. These fluctuations resulted in unwanted artifacts called musical noise [60].

It should be noted that in state-of-the-art speech enhancement algorithms (e.g. logMMSE) the *a priori* SNR is estimated in a decision-directed way [60], [59], and [61]. In general, the logMMSE NR estimates *a priori* SNR by adaptively smoothing its maximum likelihood estimate in the frequency domain.

#### 2.7.1.2 Decision-directed approach

*A priori* SNR is estimated based on a previous clean-speech estimation, $\tilde{S}(K, L-1)$ as illustrated in the Equation 2.4 [60].

$$\tilde{\xi}(K, L) = max\{\alpha dd.\frac{|\tilde{S}(K,L-1)|^2}{\tilde{\lambda}_u(K,L-1)} + (1 - \alpha dd)\tilde{\xi}^{ml}(K, L), \xi_{minm}\} \qquad (2.4)$$

where $\tilde{\lambda}_u$ is the estimated noise power, and $\tilde{\xi}^{ml}$ is the estimated ML which can be computed by estimating $\tilde{\lambda}_u$. As can be seen from the Equation 2.4, $\alpha dd$ and $\xi_{minm}$ are the parameters that can control the trade-off between the noise reduction and speech distortion.

## 2.7.2 MHA NR

The MHA NR algorithm is an example of Wiener filtering algorithms that works in the short-time Fourier transform (STFT) domain. The main difference between statistical-model-based methods and Wiener filter models is that in the latter, the goal is to estimate the complex spectrum of the speech while in the former, the focus is on estimating the magnitude of the speech spectrum [59]. The block diagram of the Wiener filter is shown in Figure 2-8, where y(n) is the noisy speech, d(n) is the clean speech, estimated y(n) is the denoised (enhanced) speech. The goal of the Wiener filter is to compute the filter coefficients to minimize the mean-square-estimation error which is computed by ($E[e^2(n)]$).

The estimation of the *a priori* SNR is a critical stage of NR algorithms [61]. Hence, an erroneous estimation of this parameter leads to speech distortion, musical noise, or reduced noise reduction especially for a non-stationary noisy environment since the estimation of the *a priori* SNR is significantly difficult [61]. In addition, the MHA NR algorithm uses temporal smoothing in the cepstral domain to conduct the estimation of the maximum likelihood estimate of the SNR. In the cepstral domain the noisy speech signal is decomposed into coefficients related mainly to the speech envelope, the excitation, and noise [60]. The coefficients that represent the speech envelope are represented by the small set of cepstral coefficients, while the coefficients that represent the excitation can be found by searching for a cepstral peak in a defined range. The remaining coefficients are dominated by noise. Hence, the selective temporal smoothing can be applied to the cepstral representation of a maximum likelihood estimate of the speech power spectral density (viz. strong smoothing to the coefficients that are dominant by noise, and little smoothing to the coefficients representing speech). Breithaupt et al. [60] showed that estimating the *a priori* SNR based on cepstral domain approach outperforms the decision-directed approach for both stationary and non-stationary noise in terms of several instrumental measures.

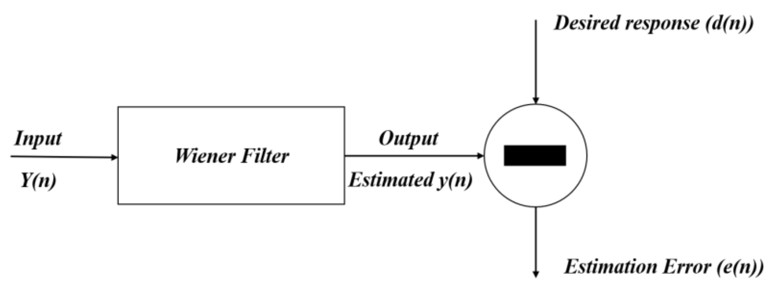



**Figure 2-8: Block diagram of a Wiener filter.**

## 2.8 Summary

This chapter presented various signal processing techniques that may be beneficial for individuals with SNHL and ANSD, followed by a literature review of previous research work conducted on these algorithms. In addition, the implementation and assessment stages of these algorithms were introduced. Furthermore, a literature review of the existing portable platforms examined, followed by an introduction of the iPad and openMHA platforms. Finally, the two objective indices (*viz*. HASPI and ModA) were introduced as metrics to predict speech intelligibility across different processing conditions in this thesis, followed by introducing the two types of NR techniques (*viz*. logMMSE and MHA) NR as front-end applications to the introduced signal processing techniques. The next chapter examines the implementation and assessment of the dynamic envelope enhancement algorithm subjectively and objectively for hearing assistive devices.

# Chapter 3

# 3 Dynamic Envelope Enhancement Algorithm

In the previous chapter, the effectiveness of the dynamic EE for speech perception in ANSD patients was discussed. In this chapter, the development and assessment of the dynamic EE algorithm for typical RM applications is investigated. Although the dynamic EE is implemented on iPad and openMHA platforms, the dynamic EE development, debugging, and testing is completed using MATLAB 2016a. It should be noted that, in this chapter, offline evaluation of the dynamic EE is considered, and realtime implementation of the dynamic EE algorithm is out of scope for the present study.

As described in the previous chapter in Section 2.1, the benefit of the dynamic EE for speech perception in ANSD has been achieved for word recognition tasks. The main goal of the present study is to evaluate the effectiveness of the dynamic EE on sentence-level speech perception for children with suspected APD across different processing conditions. It is also pertinent to point out that the dynamic EE algorithm described by Narne et al. [25] is modified for the purpose of testing at the sentence level as explained later on in this chapter. In general, this chapter contributes new results on the performance of the dynamic EE algorithms by answering the following research questions: (1) does the dynamic EE algorithm enhance speech intelligibility for children with suspected APD? (2) can a new objective speech intelligibility metric be derived to predict the perceptual impact of this type of algorithm? and (3) how does the dynamic EE perform in a variety of noisy conditions as evaluated using the new validated objective metric?

## 3.1 Implementation of dynamic EE

### 3.1.1 MATLAB implementation

The dynamic EE algorithm is depicted in the block diagram shown in Figure 3-1.

The input speech signal is split into a specified number of bands (in this case, four) by 6$^{th}$ order Butterworth bandpass filters to provide frequency-dependent processing.  This proved to provide robust and accurate results [25]. The cut-off frequencies for the bandpass filters were specified as 150-550 Hz, 550-1550 Hz, 1550-3550 Hz, and 3550-8000 Hz.

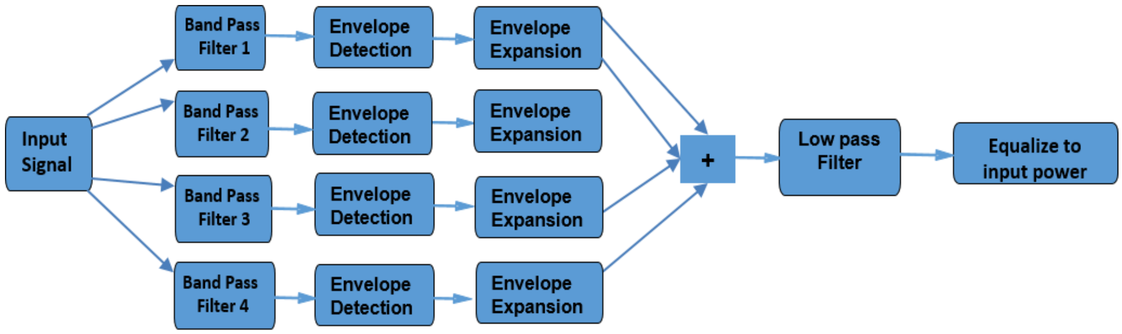



**Figure 3-1:Block diagram of the dynamic EE algorithm.**

#### 3.1.1.1 Envelope extraction

Next, the temporal envelope in each frequency channel is extracted through a combination of full-wave rectification and a first order low pass Butterworth filter with a cutoff frequency of 32 Hz as shown by Narne et.al. [25]. This cutoff frequency provided optimal results. Although it was not specified in [25], careful attention is given to the filter delay to ensure that the extracted envelope does not lag the actual envelope of the signal. Hence, the zero-phase filtering approach is applied to extract the envelope of the signal for offline evaluation of the EE algorithm. However, the zero-phase filtering technique is not practical for realtime implementation of this algorithm. While realtime implementation of the dynamic EE algorithm is out of scope for this thesis, for realtime implementation, we can refer to sample papers on this topic by Clarkson & Bahgat [62] and Koutsogiannaki et al. [63].

#### 3.1.1.2 Envelope expansion

The extracted envelope in the $i^{th}$ band is exaggerated by raising it to the power of $k_{bi}$, which is calculated in each band separately through an exponential function shown in Equation 3.1.

$$k_{bi} = e^{\frac{(E_{bmin}-E_{bi})}{\tau}}\,(k_{max}-k_{min})+ k_{min} \tag{3.1}$$

where $k_{min}$ = 0.3, $k_{max}$ = 4, $E_{bmin}$ is the minimum amplitude of the envelope in the $i^{th}$ band, $E_{bi}$ is the instantaneous amplitude value of the envelope in the $i^{th}$ band, and $\tau$ is the time constant for the exponent. It is pertinent to point out that both $k_{bi}$ and $E_{bmin}$ are calculated for each band independently.

Next, an instantaneous correction factor is obtained for each sample by computing the ratio of the expanded envelope to the original envelope. The correction factor is then multiplied with the original bandpass signal on a sample-by-sample basis to obtain the expanded signal. The individual expanded signals in the four bands are subsequently combined, and the output is filtered by a 3rd order Butterworth low pass filter with a cutoff frequency of 8000 Hz. The enhanced output is then scaled such that its Root-Mean-Square (RMS) amplitude is equated to that of the original input signal.

#### 3.1.1.3 Selection of time-constant ($\tau$)

Narne et al. [10], used a value of 0.5 for $\tau$ for all their stimuli when applying the dynamic EE algorithm. However, when applied to sentences, it was found that a value of 0.5 for $\tau$ is too large. In practice, the value of $\tau$ determines how much $k_{bi}$ will fluctuate between its minimum and maximum values as the signal amplitude changes. If $\tau$ is too large, $k$ will remain fairly constant as the exponential function decays slowly with respect to the envelope amplitude based on Equation 3.1. It should be noted that through experimentation, values of 0.00001, 0.0001, and 0.001 for $\tau$ proved to consistently produce a large variation in $k$ for the sentences used for the assessment of the dynamic EE. Figure 3-2 compares the effect of different $\tau$ values on $k$ in the 4th acoustic band (viz. 3550-8000 Hz).

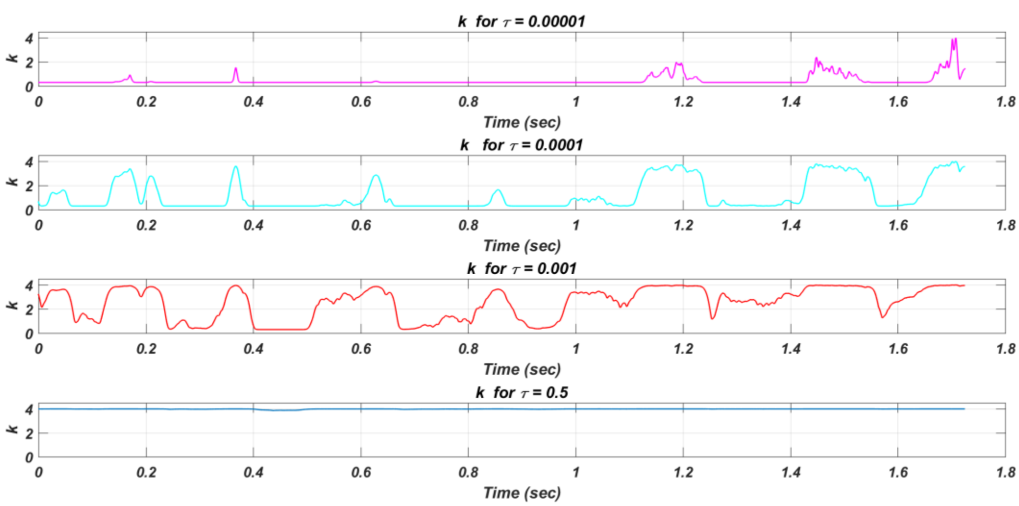



**Figure 3-2: Effect of time-constant selection ($\tau$) on $k$ variations for the stimulus "the car is going too fast".**

Furthermore, Figure 3-3 illustrates the impact of choosing different τ values on the enhancement of a sample speech envelope in the 4$^{th}$ acoustic band (viz. 3550-8000 Hz). Figure 3-3a shows the unprocessed envelope in this band, while Figure 3-3[b-d] depict the enhanced envelopes for τ = 0.00001, 0.001, and 0.5, respectively. It is evident that the first two τs exaggerate the speech envelope to different degrees, but the final τ value leads to a flattening of the envelope leading to a dramatic suppression of almost the entire speech signal. Hence, at least for sentence-level envelope enhancement, lower τ values are essential for an effective operation of the dynamic EE. It should be noted that, in Figure 3-3, the y-axis amplitude scale was deliberately left different to show the envelope variations.

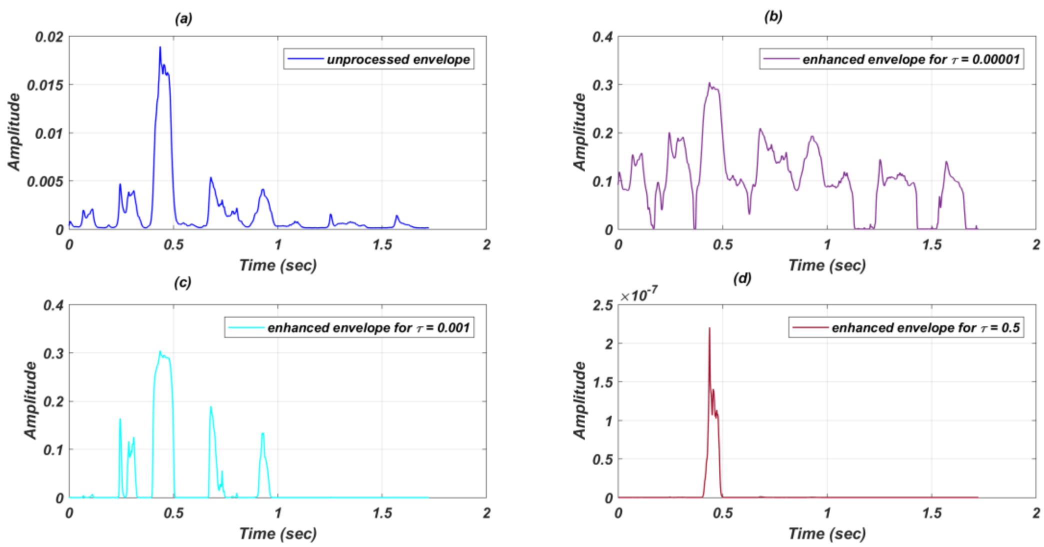



**Figure 3-3: Effect of the τ parameter on envelope enhancement in the high frequency band for a sample speech stimulus (“the car is going too fast”). (a) unprocessed envelope, (b) enhanced with τ = 0.00001, (c) enhanced with τ = 0.001, and (d) enhanced with τ = 0.5**

Figure 3-4 shows an alternative visualization of the effect of the dynamic EE algorithm. This set of plots display the modulation spectrograms which show the distribution of modulation energy as a function of the modulation frequency and acoustic frequency, averaged over all speech frames. Figure 3-4a depicts the modulation spectrogram for the unprocessed speech, where modulation energy is concentrated in the 4-10 Hz and lower frequency acoustic channels. Modulation spectrograms for the dynamic EE with τ = 0.00001, τ = 0.0001, and τ = 0.001 are shown in Figure 3-4b, c, and d, respectively, where the spread of modulation energy across mid- and high-frequency acoustic channels is apparent. It is well-known that slow temporal envelope modulations in the 4-10 Hz provide useful cues for speech perception [4]. It is evident from Figure 3-4 that the dynamic EE algorithm exaggerates these useful cues.

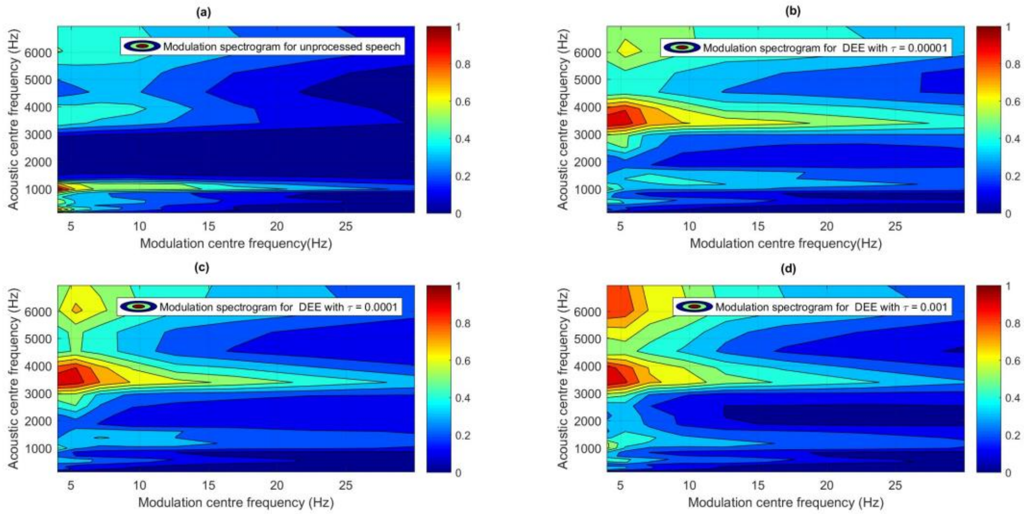



**Figure 3-4: Modulation spectrograms for the original and enhanced speech samples. (a) original speech, (b) dynamic EE with τ = 0.00001, (c) dynamic EE with τ = 0.0001, and (d) dynamic with τ = 0.001.**

## 3.2 iPad implementation

The dynamic EE algorithm was implemented for an iPad platform as an iOS application for offline processing as mentioned in the previous chapter. The application is developed by converting the MATLAB script of dynamic EE line-by-line into Swift programming by utilizing Xcode as an IDE and the VDSP portion of the Accelerate Framework [55]. As we mentioned in the previous chapter, the iPad platform development of the dynamic EE is motivated since our centre at the Western University (National Centre for Audiology) has developed a software to conduct the temporal modulation test on the iPad platform. Hence, integrating the dynamic EE algorithm within the temporal modulation test on the iPad platform allows a clinician to change the τ parameter of the dynamic EE to compensate the patient's temporal modulation deficit.

Figure 3-5 is an example stimulus that shows the dynamic EE output speech based on iOS implementation, which is identical to the dynamic EE output speech generated from MATLAB. In order to verify that the implemented dynamic EE based on the iOS generates the same output as the MATLAB implementation, the output speech file from iOS is first converted to binary file. Then, the binary file from iOS is loaded in MATLAB.

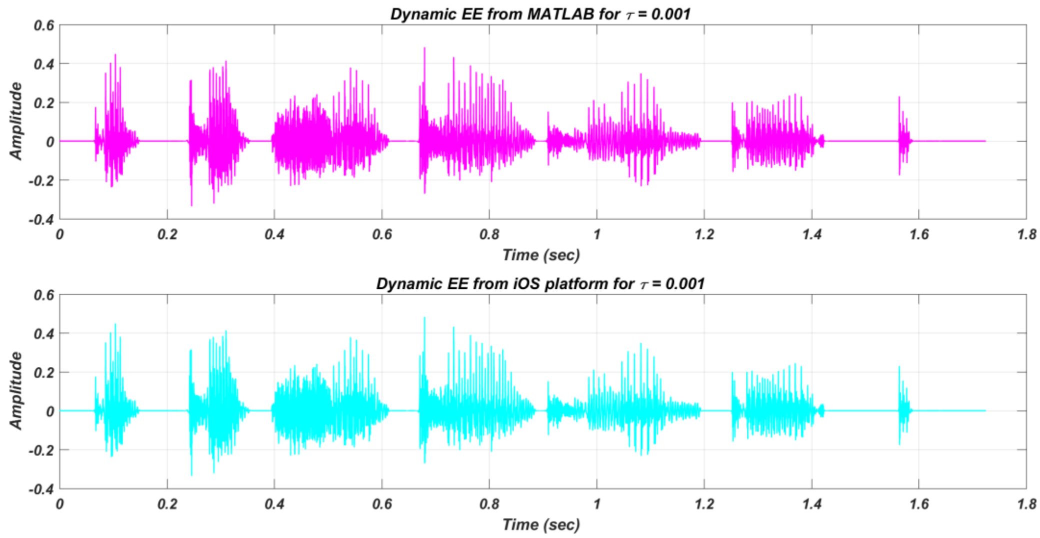



**Figure 3-5: Comparison of the dynamic EE speech stimulus between MATLAB and iPad platforms.**

## 3.3 OpenMHA implementation

As we mentioned in the first chapter of the thesis, the dynamic EE is also implemented as a signal processing plugin into an openMHA platform for offline processing. This implementation is motivated due to the fact that we can use a single-channel noise reduction plugin of openMHA (viz. MHANR) as a front-end to the application of the dynamic EE. It is well- known that for hearing aid applications, the proper strategy is to first separate speech from noise and then enhance the envelope of the speech because background noise reduces the modulation depth and creates spurious modulations to the speech signal [25]. Hence, we do not need to consider the implementation of an extra NR block as *a priori* processing block to the dynamic EE processing block for both offline and online processing stages of the dynamic EE into openMHA platform.

Dynamic EE is implemented as a new plugin for the openMHA similar to its MATLAB implementation. The dynamic EE plugin is implemented by defining it as a C++ class, which is derived from a generic base class, followed by implementing its methods and compiling to a shared object. As mentioned in the previous chapter, the computational complexity of the dynamic EE implementation managed through the use of optimized IPP functions.

Figure 3-6 is an example stimulus which shows that the dynamic EE output speech based on openMHA platform is identical to the dynamic EE output speech generated from MATLAB. In order to verify that the developed dynamic EE based on openMHA platform generates the same output as the MATLAB development, the output speech file from the openMHA platform is first converted to binary file. Then, the binary file from the openMHA platform is loaded in MATLAB.

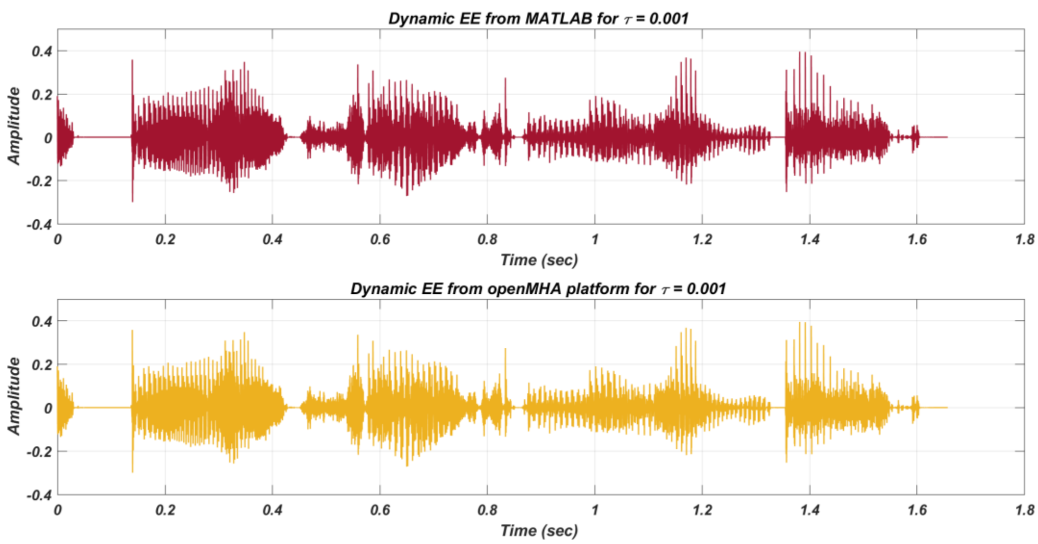



**Figure 3-6: Comparison of the dynamic EE speech stimulus between MATLAB and openMHA platforms.**

As we mentioned earlier in section 3.1 of this chapter, the assessment and evaluation of the dynamic EE is performed based on its MATLAB implementation for offline processing.

## 3.4 Subjective data collection for the dynamic EE

### 3.4.1 Database

A noisy speech database was created for collecting the speech intelligibility data from the participants. The clean speech sentences were taken from the HINT database [28] which contains 25 lists of 10 sentences each that are phonetically balanced and considered equally difficult. It should be noted that the clean speech samples taken from the HINT speech database have an original sampling rate of 44100 Hz which were subsequently down-sampled to 16000 Hz for our application. The clean speech sentences were passed through the dynamic EE algorithm with varying values of $\tau$. No background noise was added prior to the application of the dynamic EE algorithm, while the HINT background noise (speech-shaped noise or SSN) was mixed in at different SNRs after enhancement, which is defined as the LSNR. In total, the database comprised of 25 HINT lists x 10 sentences per list x 4 $\tau$ values ( $\tau$ = 0.00001, 0.0001, 0.001, and unprocessed) x 4 LSNRs (3 dB, 0 dB, -3 dB, and -6 dB) = 4000 stimuli.

### 3.4.2 Participants

The dynamic EE algorithm was evaluated subjectively by three different groups of participants: 11 children with suspected APD, 12 children with normal hearing (NH), and 12 adults with NH. The children with normal hearing ranged between 8-15 years in age, while the adults ranged between 18-30 years. The normal hearing groups had no history of any auditory problems or listening difficulties. The children with suspected APD ranged between 7-15.5 years and were referred to the Audiology clinic at the University of Western Ontario based on complaints of listening difficulties by their parents or teachers. It should be noted that these children did not undergo the test battery recommended by the American Speech and Hearing Association (ASHA) [64].

### 3.4.3 Audio presentation and speech intelligibility measurement

Speech perception in noise was measured using custom software developed in our laboratory. Speech stimuli were played via the interface shown in Figure 3-7. Participants were seated in a double-walled sound booth and listened to stimuli over Sennheiser HDA 200 headphones at the most comfortable level. Participants were told that they would hear sentences in background noise, and they would hear each sentence just once. The participants had to repeat the speech token heard by them and the number of correctly reported key words were logged before presenting the next sentence in the list. It can be observed from Figure 3-7 that each word has an equal score in terms of intelligibility, and the averaged speech intelligibility score for each condition was computed by averaging the scores from ten sentences in a randomly selected list. It is also pertinent to point out that to ensure that fatigue was not a confound, this experiment lasted about half-an-hour and participants were encouraged to take break if they felt fatigued.

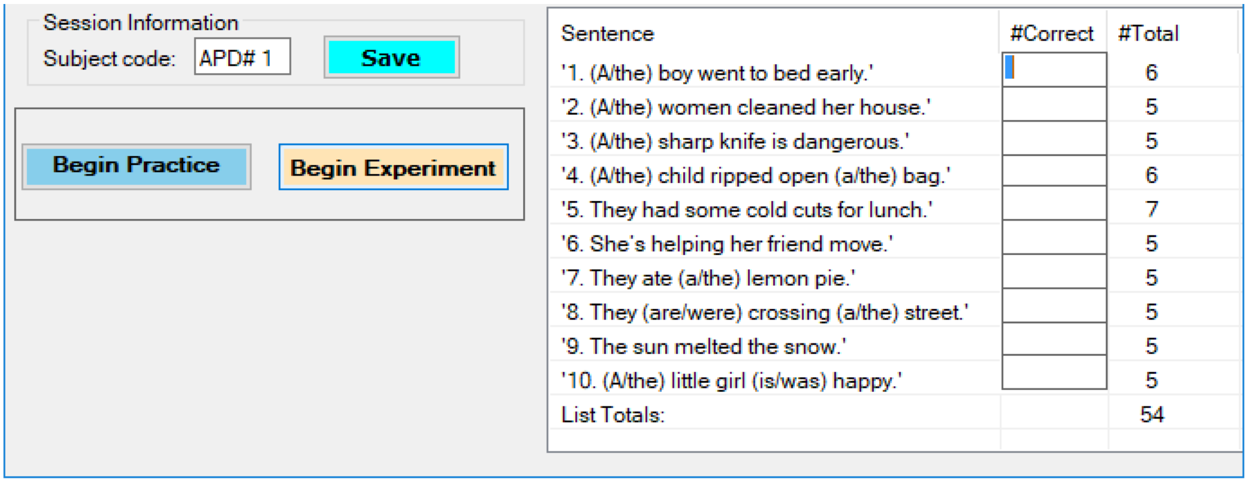



**Figure 3-7: Graphical user interface (GUI) for collecting speech intelligibility scores from participants.**

## 3.5 Subjective score analysis

Figure 3-8 – Figure 3-10 depict the averaged speech intelligibility scores for children with suspected APD, adults with normal hearing, and children with normal hearing respectively, where the "up" and "Tau" conditions represent the unprocessed and dynamic EE speech with different time-constant ($\tau$ ) values that were mixed with background noise at different SNR values respectively. In these figures, the error bars represent one standard deviation. The subjective results in Figure 3-8 – Figure 3-10 demonstrate the benefits accrued from the dynamic EE algorithm regardless of the LSNR condition and participant groups. The amount of improvement was significantly better for poorer LSNRs (i.e., LSNR = -3 and LSNR = -6 dB) across groups. The results also demonstrate that for all groups, $\tau$ (Tau = 0.0001) achieved the highest speech intelligibility mean scores for LSNR = 3, 0, and -3 dB conditions. On the other hand, $\tau$ (Tau = 0.00001) achieved the highest speech intelligibility mean score, but only for LSNR = -6 dB condition. In order to quantify the significance of these differences, a thorough statistical analysis was performed.

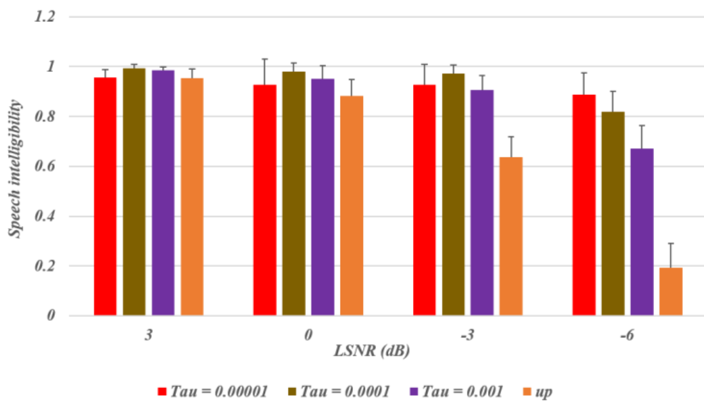



**Figure 3-8: Averaged speech intelligibility scores for children with suspected APD.**

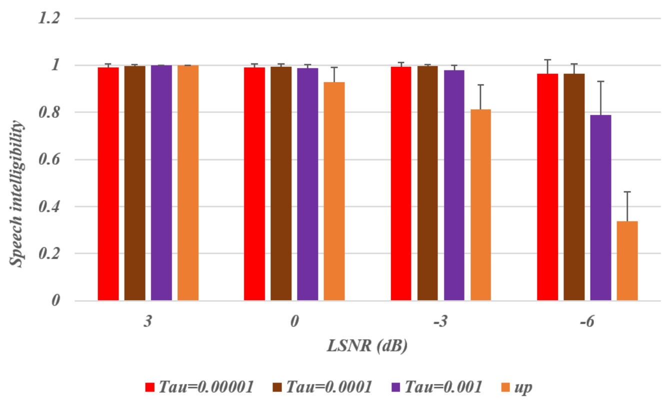



**Figure 3-9: Averaged speech intelligibility scores for adults with NH.**

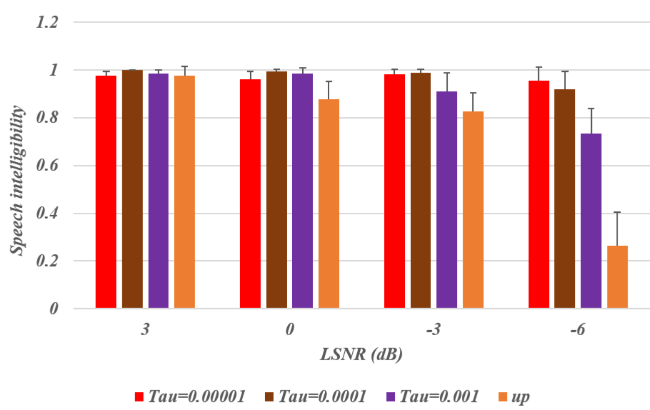



**Figure 3-10: Averaged speech intelligibility scores for children with NH.**

## 3.6 Statistical analysis

To determine whether these differences are statistically significant, repeated measures ANOVA was conducted with the results obtained from the children with normal hearing and children with suspected APDs using IBM SPSS software, Version 25.0. It should be noted that the raw scores were first transformed to rationalized arcsine units (RAUs). The rationalized arcsine transform is used to transform data obtained from speech intelligibility tests in order to make them suitable for parametric statistical analyzes [65]. Studebaker [65] proposed equations to perform RAUs: (1) arcsine unit transform equation, as shown in Equation. 3.2, where s is the number of correct responses and N is the number of trials performed, (2) Rationalized arcsine units transform equation, which converts radians into RAUs, shown in Equation 3.3.

$$Au = sin^{-1}\sqrt{\frac{s}{N+1}} + sin^{-1}\sqrt{\frac{s+1}{N+1}} \tag{3.2}$$

$$RAUs = \left(\frac{146}{\pi}\right) * Au - 23 \tag{3.3}$$

The repeated measures ANOVA was performed with $\tau$ and LSNR as the within-subject factors. It should be noted that Mauchly's test of sphericity was violated for the LSNR variable ($\chi^2(5) = 12.43$, $p =.03$), so the Greenhouse-Geisser correction was used for this condition ($\varepsilon = 0.71$). There were significant main effects of $\tau$ ($F(3, 63) = 218.47$, $p < 0.001$) and LSNR ($F(2.12, 44.58) = 284.27$, $p < 0.001$) parameters. There was no statistically significant interaction between the $\tau$, LSNR parameters and the subjective group (normal vs. suspected APD), indicating that changing the $\tau$ and LSNR values had a similar effect across both groups. There was a significant interaction between $\tau$ and LSNR variables ($F(9, 189) = 47.45$, $p < 0.001$), suggesting that the relative performance of the dynamic EE for a given $\tau$ depended on the LSNR.

To further probe this interaction, post-hoc comparisons between the subjective data at different $\tau$ and LSNR values were conducted with Bonferroni correction. Salient outcomes of this analysis include: (i) the scores associated with $\tau = 0.0001$ were significantly better than unprocessed scores at all LSNRs, whereas $\tau = 0.00001$ and $\tau = 0.001$ were better only at LSNRs of -6 and -3 dB respectively; and (ii) the performance of $\tau = 0.00001$ and $\tau = 0.0001$ was statistically similar at LSNRs -3 and -6 dB, while $\tau = 0.0001$ is statistically better than $\tau = 0.00001$ at LSNRs of 0 and 3 dB. It should be noted that SPSS outputs from subjective experiment of the dynamic EE algorithm can be found in Appendix A of this thesis.

## 3.7 Objective evaluation

### 3.7.1 Subjective vs. objective measures

An ideal objective metric should be able to predict the subjective speech intelligibility scores with high accuracy. Various statistics can be conducted to evaluate the performance of the objective metrics. The two most common ones are Pearson's correlation coefficient ($\rho$) and the standard deviation of error [66], which were used to evaluate the performance of the two-objective metrics (viz. HASPI and ModA). The correlation coefficient between the subjective speech intelligibility scores ($S_I$) and the objective speech intelligibility scores ($O_I$) is computed by Equation 3.4, where $MS_I$ and $MO_I$ are the mean values of $S_I$ and $O_I$ respectively. An estimation of the standard deviation of the error ($\sigma_e$) is computed by Equation 3.5, where $\sigma_d$ is the standard deviation of subjective scores. A good objective metric should yield a high correlation value and a small value of $\sigma_e$.

$$\rho = \frac{\sum(S_I - MS_I)\cdot(O_I - MO_I)}{[\sum(S_I - MS_I)^2]^{1/2}.\ [\sum(O_I - MO_I)^2]^{1/2}} \tag{3.4}$$

$$\sigma_e = \sigma_d.\sqrt{1-\rho^2} \tag{3.5}$$

### 3.7.2 First stage

As mentioned in the introduction chapter, benchmarking the dynamic EE across several noisy conditions can become an onerous task. Hence, in the first stage of the objective assessment of the dynamic EE, both HASPI and ModA objective indices were applied to predict the speech intelligibility for dynamic EE algorithm across the same processing conditions used during the subjective assessment (viz. the stationary background noise at different LSNR was added after the envelope was enhanced). The computation of HASPI and ModA were based on the MATLAB code provided by Kates [30] and Chen et al. [31]. A correlation analysis was conducted in such a way that, HASPI and ModA scores were computed 176 times (11 APD subjects x 16 processing conditions [4 processing ($\tau$ = 0.00001, $\tau$ = 0.0001, $\tau$ = 0. 001, and UP) x 4 SNRs (3, 0, -3, and -6 dB)] to match with the 176 subjective data points for correlation analysis. A list of ten sentences was randomly selected from the SSN database for each processing conditions, and the objective speech intelligibility predictors (HSPI and ModA) were computed from all ten sentences in the list. Table 3.1 shows the correlation coefficients and the standard errors of estimation for HASPI and ModA metrics. It can be noted from Table 3.1 that HASPI exhibited higher correlation with the suspected with

APD subjective scores compared to ModA. Figure 3 – 11 depicts the scatter plot of the objective speech intelligibility scores versus the actual suspected with APD subjective scores.

**Table 3-1: Correlation coefficient and standard error of estimation for HASPI and ModA.**

| Objective measure | $\rho$ | $\sigma_e$ |
|---|---|---|
| HASPI | 0.72 | 0.15 |
| ModA | 0.38 | 0.19 |

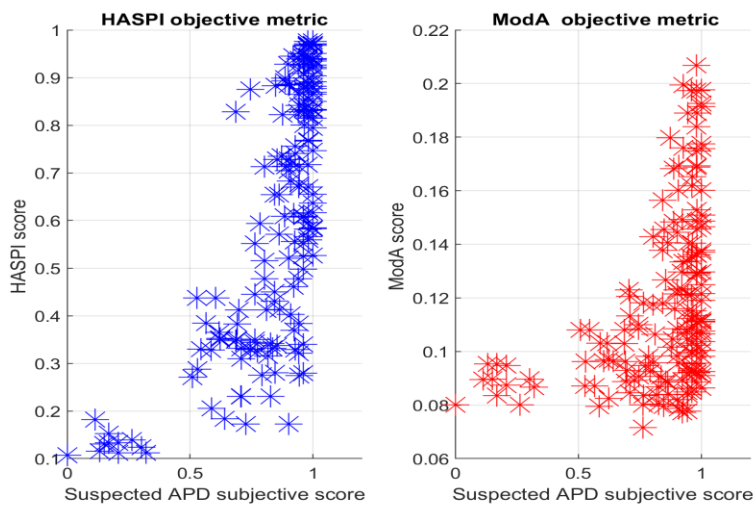



**Figure 3-11: Scatter plot of the objective and subjective scores from children suspected with APD for HASPI and ModA.**

### 3.7.3 Second stage

Since HASPI correlated higher with the subjective scores from children suspected with APD, it can be used to evaluate the performance of dynamic EE algorithm across several noisy conditions. However, to find a better mapping between HASPI and subjective data, a new objective predictor is derived in a similar manner to HASPI objective metric. As we discussed in Chapter 2, section 2.6.1, HASPI score is computed from the raw features of HASPI (e.g. cepstral correlation (c) and three-level temporal fine structure covariances ($a_{Low}$, $a_{Mid}$, and $a_{High}$)), as was shown in Equation 2.1. Hence, in the second stage of the objective assessment, a modified HASPI metric was derived by computing HASPI features (i.e. c, $a_{Low}$, $a_{Mid}$, and $a_{High}$) for each processing condition [viz. 176 scores (11 subjects with suspected APD x 16 processing conditions)]. Then, the optimal combination of the HASPI features was derived through multivariate regression analysis, which estimates a regression model with more than one outcome variable. It should be noted that multivariate regression analysis was conducted, by utilizing the "Regression Learner" feature in MATLAB. It is also important to note that "Regression Learner" application in MATLAB predicts data using supervised machine learning algorithms. The "Regression Learner" application trains regression models to predict data. The HASPI features and the subjective scores from children suspected with APD are defined as predictors and response variables respectively to the regression model. It also should be noted that automated training was performed to search for the best regression model type, the one that achieves the lowest value of root mean square error (RMSE, which is the square root of the variance of the residuals). After training a model in "Regression Leaner" application in MATLAB, a regression tree model achieved the lowest RMSE value, which was 0.0718. It is worthwhile to mention here that the decision tree (DT) builds regression or classification hierarchical models in the form of a tree structure. It is defined as a classification or a regression when the target variables are discrete or continues respectively [66]. The objective of DT building is to breaks down a dataset into smaller and smaller subsets in order to be used to predict outcome (target) from a set of input variables. The final result is a tree with decision nodes and leaf nodes. A decision node (e.g., HASPI features) has 4 branches in our experiment data, each representing values for the attribute (i.e. speech intelligibility) tested. Leaf node (e.g., suspected with APD intelligibility scores) represents a decision on the numerical target. The topmost decision node in a tree, which corresponds to the best predictor, called root node. It is important to note that a decision tree is built top-down from a root node and involves partitioning the data into subset that contain instances with similar values (homogenous) [67].

In the present mapping, the regression tree model explained 88% of the variance in the subjective data, which is defined as R-squared. It should be noted that a well-fitting regression model results in predicted values close to the observed data values. This parameter can be interpreted as the standard deviation of the unexplained variance. Lower values of RMSE indicate better fit, and RMSE is a good measure of how accurately the model predicts the subjective scores. In addition, R-squared, which indicates the percentage of the response variable variation that is explained by a fitted model, is another statistical measure of how close the data are to the fitted regression line. The trained model (regression tree) based on the suspected with APD scores is termed as 'dynamic EE data trained (DEEDT)' model for the rest of this thesis.

### 3.7.4 Testing the DEEDT model

In order to show how accurate our intelligibility predictor model is, the raw features of HASPI were computed for each corresponding subjective score from adults and children with normal hearing, who were participating in our subjective experiment. The computed raw features were then given to DEEDT model to predict the subjective scores for both adults and children with normal hearing participants. Scatter plots of predicted versus subjective scores for adult and children with normal hearing can be noted from Figure 3-12. The robustness of the fitted (DEEDT) model can be seen from Table 3.2, which shows the correlation coefficient and the standard error of estimation for adults and children with normal hearing participants. In addition, the DEEDT model explains 0.82 and 0.83 of the variability of the subjective data for adult and children with normal hearing respectively.

**Table 3-2: Correlation coefficient and standard error of estimation for HASPI and ModA.**

| DEEDT predicted scores | $\rho$ | $\sigma_e$ |
|---|---|---|
| Children with normal hearing | 0.91 | 0.08 |
| Adults with normal hearing | 0.91 | 0.07 |

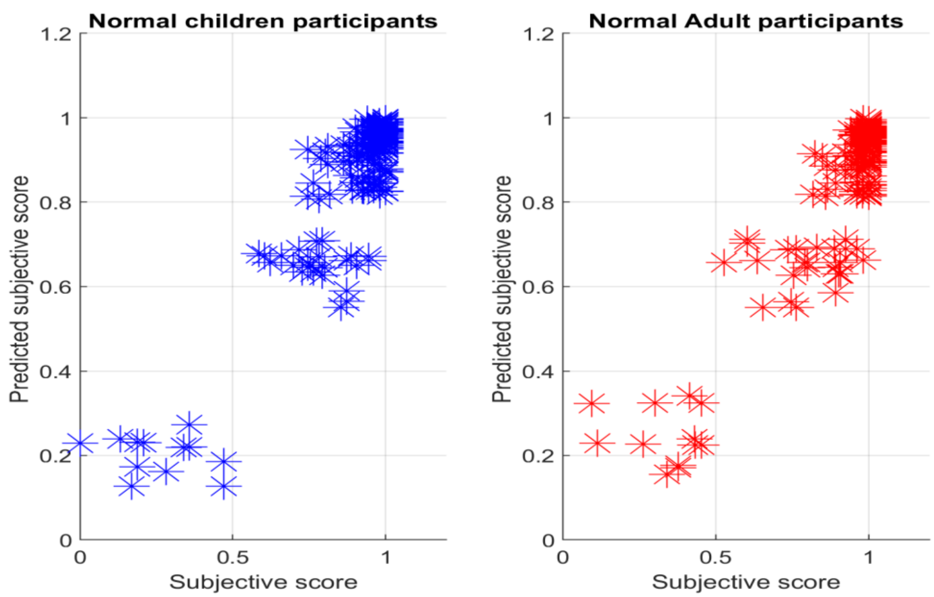



**Figure 3-12: Scatter plot of predicted and subjective scores for children and adults with normal hearing participants.**

### 3.7.4.1 Bland- Altman plot

Although the predicted subjective scores showed an excellent correlation with actual subjective scores, higher degree of correlation does not imply the agreement between the predicted and actual subjective scores. The Bland-Altman plot, or difference plot, is a graphical method for analyzing agreement between two measurement methods. This technique was applied in a recent research study to indicate the agreement between predicted and measured speech intelligibility in non-stationary real-world noise environment by utilizing HINT sentence list database [68]. Hence, in this thesis, the agreement between the predicted subjective scores and the actual subjective scores was evaluated using Bland-Altman plot. In this graphical analysis, the difference between the two techniques are plotted against the averages of the two techniques. Horizontal lines are drawn at the mean difference, and at the limits of agreement (95% confidence intervals), which are defined, as shown in Equation 3.6, where *m* and *sd* represent the mean and the standard deviation of the difference respectively.

$$limits\ of\ agreement = [m +/-(1.96 * sd)] \qquad (3.6)$$

Figs 3-13 and 3-14 display the Bland-Altman plots for adults and children with normal hearing subjective scores, respectively. The x axis displays the percentage average of the predicted and subjective scores, and the y axis displays the percentage difference between these scores. For both figures, the centre line, which is highlighted as a red line, is plotted at the mean of the difference between the predicted and subjective intelligibility scores. In addition, the upper and lower lines, which are highlighted as green lines, are plotted at the bound of 95% confidence interval levels (CIL). A mean difference score that differs from zero is evidence of bias in the predictor [68]. It is important to note that for Figs 3-13 and 3-14 the mean difference scores were 7.05 % and 4.47 % respectively, which are within the measurement error of the HINT [68]. The 95 % CI width for Figs 3 – 13 and 3 – 14 are 15.51 % and 16.23 % respectively, which are again comparable to the HINT's test-retest reliability [68] and [69].

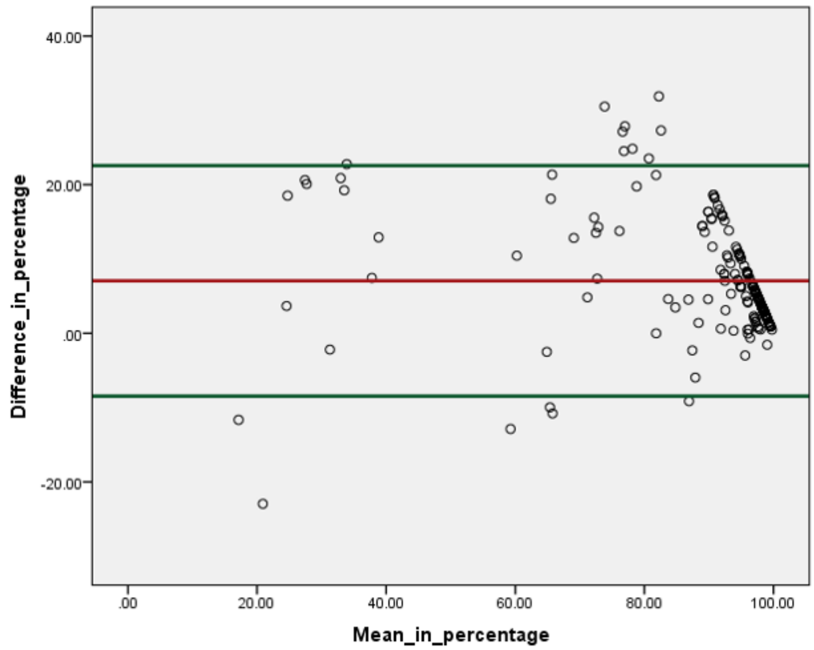



**Figure 3-13: Bland-Altman plot (adults with normal hearing subjective scores versus predicted scores).**

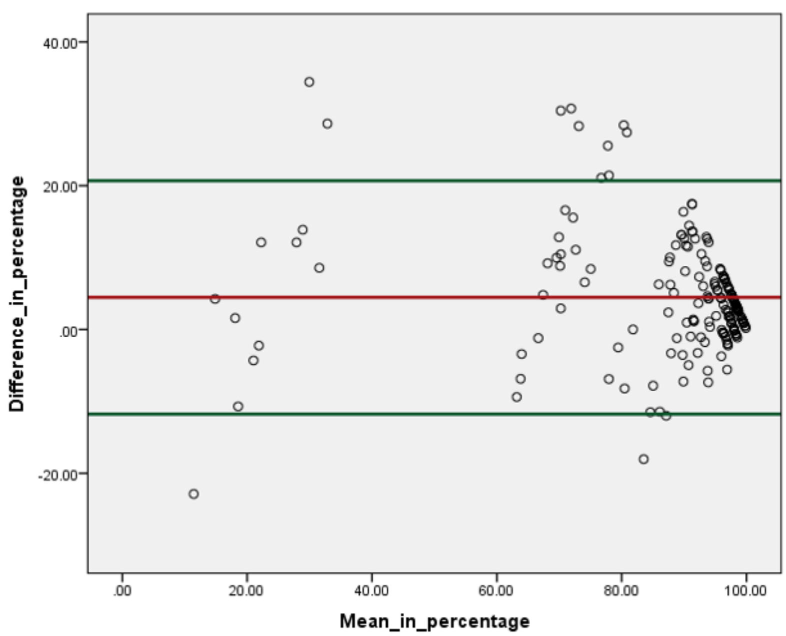



**Figure 3-14: Bland-Altman plot (children with normal hearing subjective scores versus predicted scores).**

## 3.8 Comprehensive objective assessment

Previous studies performed limited evaluation of the effect of background noise on the performance of the dynamic EE algorithm by making an assumption that a remote microphone is close to the speech source. Hence, relatively clean speech picked up by the microphone is transmitted to a receiver of a hearing aid, and the background noise is only added after enhancing the envelope of the speech. However, as described in the previous chapter, section 2.1.3 (see Figure 2-2), the background noise can be present at the source (i.e. before EE) and/or at the listener (i.e. after EE). In addition, the background noise can be stationary or non-stationary. It is therefore imperative to benchmark the algorithm performance under different source and listener SNRs (SSNRs and LSNRs respectively) as well as different types of background noise.

For a comprehensive benchmarking of the dynamic EE algorithm, a larger HINT database was created. First, the clean HINT speech sentences were mixed separately with two different background noise types (viz. HINT speech-shaped-noise (SSN) and multi-talker-babble-noise (MTBN)) at different SSNRs. The noisy speech stimuli were then processed by the dynamic EE algorithm. Different $\tau$ values were chosen in a manner similar to the subjective study. The enhanced speech was further corrupted, again separately, by SSN and MTBN noise types at various LSNRs. Furthermore, in order to assess the benefits of incorporating NR algorithms, the logMMSE and MHA NR algorithms were applied to the noisy speech prior to the application of the dynamic EE. Hence, a total of 25 lists x 10 sentences/list x 4 EE settings (dynamic EE with $\tau$ = 0.00001, 0.0001, 0.001, and unprocessed) x 4 SSNRs ( 15 dB, 10 dB, 5 dB, and 0 dB) x 4 LSNRs (3 dB, 0 dB, -3 dB, and -6 dB) x 2 background noise (SSN and MTBN) = 96000 stimuli in the second database.

In this section, the objective assessment was carried out in a manner similar to the first stage, wherein a list of 10 sentences was randomly chosen from the new database (viz. the database was introduced in the previous paragraph) for each processing condition. Then, HASPI features (c, $a_{Low}$, $a_{Mid}$, and $a_{High}$) were computed from all 10 sentences in the list. After that, the computed features from all 10 sentences for each processing conditions were applied to the DEEDT model defined in section 3.4.3. Finally, the average score across these 10 sentences for each processing condition, which was predicted by the DEEDT model, was used for benchmarking the dynamic EE algorithm.

### 3.8.1 Comprehensive objective assessment results

The comprehensive objective assessment allowed the benchmarking of the performance of the dynamic EE across a wide range of noise conditions. However, this section includes a limited set of representative results, and the remainder of the results is available in Appendix B of this thesis.

Figures 3-15 and 3-16 display the sample result for LSNR = -6 dB (i.e. the worst-case value of the LSNR), for a range of SSNR values between 0-15 dB, when the background noise is SSN and MTBN respectively, and no NR algorithms were applied as a front-end to the dynamic EE algorithm. The Tau ($\tau$) value represents the time constant for the dynamic EE algorithm, and "up" is an unprocessed condition. The dynamic EE can be seen to be more effective for high SSNR values (i.e. 15 dB and 10 dB) when compared to the unprocessed condition. However, the lower SSNR values leads to a degradation of the dynamic EE algorithm performance, especially at lower $\tau$ values. This effect is pronounced with stationary speech-shaped noise than the multi-talker babble. Since the noise is added prior to envelope enhancement, the SSN envelope normalizes the clean speech envelope more at the lowest SSNRs, and aggressive enhancement of this noise- corrupted envelope through a lower $\tau$ value leads to a significant drop in predicted intelligibility scores.

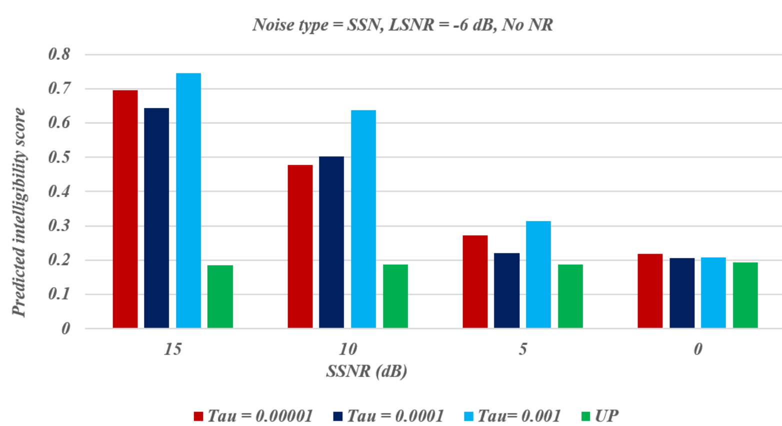



**Figure 3-15: Objective assessment of the dynamic EE algorithm for LSNR = -6 dB and for various values of SSNR, Speech-shaped noise, no NR algorithm.**

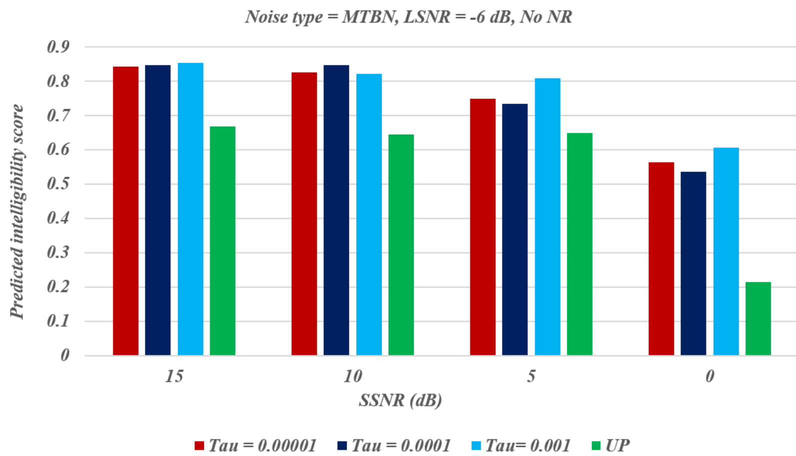



**Figure 3-16: Objective assessment of the dynamic EE algorithm for LSNR = -6 dB and for various values of SSNR, Multi-talker babble noise, no NR algorithm.**

Figures 3-17 and 3-18 also display the sample result for LSNR = -6 dB (i.e. the worst-case value of the LSNR), for a range of SSNR values between 0-15 dB, when the background noise is SSN and MTBN respectively, and the logMMSE NR algorithm was applied as a front-end to the dynamic EE algorithm. Again, the Tau (τ) value represents the time constant for the dynamic EE algorithm, and "up" is an unprocessed condition. It is evident that incorporating the logMMSE NR algorithm as a front-end to the dynamic EE algorithm results in improved predicted speech intelligibility scores, especially for lower values of SSNR. As the logMMSE NR works best with stationary noise sources [59], the improvement is more marked for the SSN condition. The interaction between the source noise and the dynamic EE's τ parameter still remains after the logMMSE NR for lower SSNR values. In general, predicted intelligibility scores are better with τ = 0.001 than the other two τ values with the activation of the logMMSE NR algorithm. While this is in contrast with the subjective results, where the lower τ values resulted in better performance, it must be noted that there was no noise added to the speech signal prior to the dynamic EE algorithm for the subjective data collection.

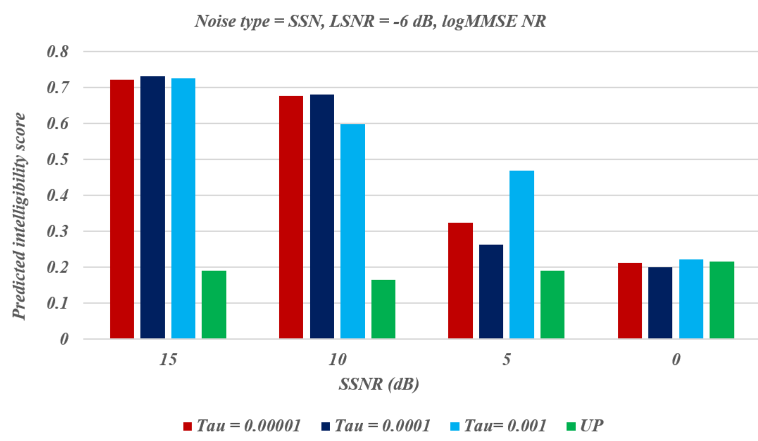



**Figure 3-17: Objective assessment of the dynamic EE algorithm for LSNR = -6 dB and for various values of SSNR, Speech-shaped noise, logMMSE NR algorithm.**

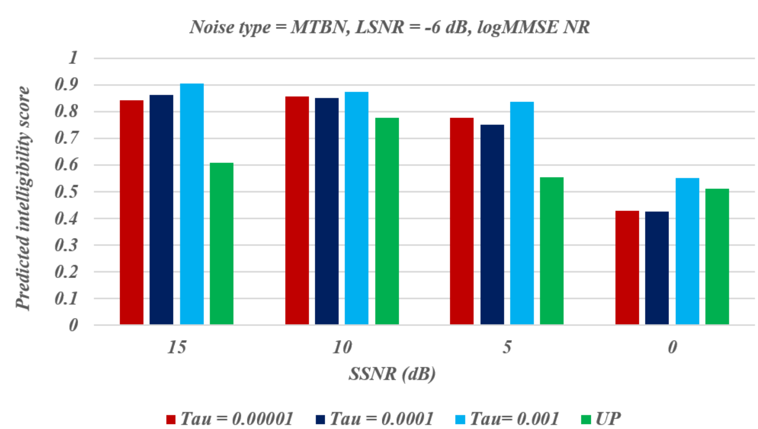



**Figure 3-18: Objective assessment of the dynamic EE algorithm for LSNR = -6 dB and for various values of SSNR, Multi-talker babble noise, logMMSE NR algorithm.**

In addition, Figures 3-19 and 3-20 display the sample result for LSNR = -6 dB (i.e. the worst-case value of the LSNR), for a range of SSNR values between 0-15 dB, when the background noise is SSN and MTBN respectively, and the MHA NR algorithm was applied as a front-end to the dynamic EE algorithm. Again, the Tau ($\tau$) value represents the time constant for the dynamic EE algorithm, and "up" is an unprocessed condition. It is evident from the predicted results that the performance of the MHA NR algorithm is pretty similar to the logMMSE NR regardless of the SSNR values and noise types.

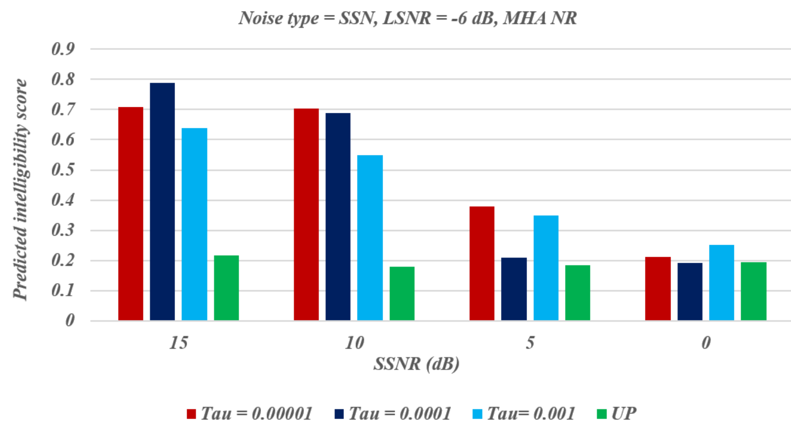



**Figure 3-19: Objective assessment of the dynamic EE algorithm for LSNR = -6 dB and for various values of SSNR, Speech-shaped noise, MHA NR algorithm.**

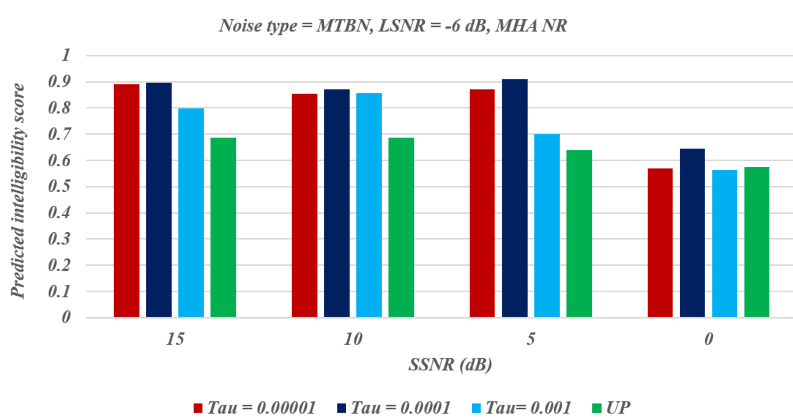



**Figure 3-20: Objective assessment of the dynamic EE algorithm for LSNR = -6 dB and for various values of SSNR, Multi-talker babble noise, MHA NR algorithm.**

## 3.9 Discussion

This study contributed several new results on the benefits of temporal speech envelope enhancement for assistive hearing device applications. In general, this study has shown that dynamic EE algorithm can enhance speech perception in noise for children with suspected auditory processing disorder, provided that the enhancement was applied to the clean speech. The study also derived a data-driven intelligibility predictor model, which correlated well with subjective scores, and utilized it for a more comprehensive benchmarking of the dynamic EE algorithm. These salient results are discussed in the next paragraphs.

### 3.9.1 Subjective and objective data

Subjective speech perception experiments showed that children with suspected auditory processing deficits perform poorly in noisy environments, particularly at inferior SNRs, as reported in the literature (e.g. [8]). To the best of our knowledge, this study is the first one to show that these children do benefit from dynamic envelope enhancement. The amount of benefit accrued through the dynamic EE algorithm was greatest for the children with suspected APD. Overall, these results are consistent with the results reported by Narne et al. [25] for adults with late onset ANSD.

This study also investigated objective, computational predictors of subjective speech recognition performance. In particular two metrics, viz. HASPI and ModA, were explored as they have been previously validated with speech recognition data from hearing impaired listeners and cochlear implant subjects. Our analyses showed that HASPI had a better correlation with subjective scores. It was surprising to see a lower degree of correlation between ModA and the subjective scores. As ModA quantifies the modulation spectrum area, it was hypothesized that enhancing the modulations would lead to a higher ModA score for enhanced stimuli, resulting in a better correlation with subjective data. Further research work is therefore conducted for improving the ModA measurement procedure for this particular application, as will be discussed in Chapter 5 of this thesis.

Although the raw correlation between HASPI and subjective scores was good, a modified HASPI model (DEEDT) was derived to better describe the relationship between the objective and subjective data. The DEEDT model was employed to further benchmark the dynamic EE algorithm across a wide range of conditions which would have been taxing for the child participants if subjective data were instead collected. This approach is a novel contribution to the dynamic EE algorithm assessment, but objective metrics have been employed before for evaluating hearing aid algorithms. For example, Kates [70] used speech quality and intelligibility metrics to assess single microphone noise reduction algorithms.

### 3.9.2 Dynamic EE algorithm, their parameters, and interaction with noise type and SNR

In general, it can be observed from the experimental results that the performance of the dynamic EE algorithm primarily depends upon the SSNR parameter and the type of the background noise. These critical parameters were not explored fully in previous research [10]. Furthermore, the results suggested that incorporating the dynamic EE strategy that enhances slow modulations in speech signal is beneficial for individuals with auditory processing deficits at the poorest LSNR condition (e.g. LSNR = -6 dB) and the highest SSNR values (e.g. SSNR = 15 dB) irrespective of the type of background noise. However, the improvement observed was significantly less for the MTBN condition when compared to the SSN condition, owing to the disparate envelope characteristics for these two noise types.

It is interesting to see that the predicted speech intelligently scores are higher for MTBN than for the SSN. This is in line with previous reports revealing the results from normal and hearing-impaired adults and children. Speech-shaped noise provides consistent spectral masking, while MTBN allows for both spectral and temporal release from masking [71].

One more observation from the results indicates that the effects of the time constant value ($\tau$), which impacted the modulation depth, is dependent on the type of the background noise. For SSN, $\tau = 0.001$ achieves higher predicted subjective mean scores in terms of speech intelligibility when compared to the two other $\tau$ values irrespective of the SSNR condition. On the other hand, when the background noise is MTBN, there are no significant differences observed in terms of the predicted subjective scores between three different $\tau$ values regardless of the SSNR condition. It should be mentioned that the amount of modulation boost that is applied by conducting dynamic EE is mostly depend upon the $\tau$ value, and it seems that modulation depth is not the same for different types of background noise due to their different envelope structures.

### 3.9.3 Effect of the NR algorithms

As the performance of the dynamic EE is affected by the presence of noise before enhancement, it is logical to consider noise mitigation prior to dynamic EE. Indeed, Narne et al. [25] surmised that a noise reduction front-end would be beneficial for the dynamic EE algorithm, although no data were presented. Similarly, Kuk [20] showed that children with APD performed better with directional microphone processing and NR. The present study employed well-known NR algorithms, the logMMSE as well as the MHA NR algorithm, to reduce the noise prior to the dynamic EE. Results showed that this strategy is beneficial, more so when the background noise is stationary and a proper $\tau$ value was selected for the dynamic EE algorithm.

Finally, the data presented in this chapter are helpful in developing initial general recommendations on when the dynamic EE can be expected to be beneficial in assistive hearing applications. It is evident from the subjective and objective data that most benefit from the dynamic EE algorithm is accrued when the SSNR is high and when the LSNR is poor. This suggests that the dynamic EE algorithm is most suited for implementation within a RM. Most modern RMs (such as Oticon Amigo and Phonak Roger) have the ability to estimate the SNR at the transmitter (i.e. SSNR) and thus can identify environmental conditions with high SSNR. Similarly, modern hearing aids incorporate automatic environment classification algorithms which estimate the type and level of the background noise at the listener to be subsequently used in decision making on the activation of the dynamic EE algorithm.

## 3.10 Summary

The present chapter reported the performance of the dynamic EE algorithm for remote microphone applications. In particular, subjective and objective experiments were conducted to investigate the performance of the dynamic EE algorithm. The subjective assessment was conducted to explore the performance of the dynamic EE algorithm in terms of the mean speech intelligibility scores in the presence of background noise at the listener location. The balance of the experiments was conducted to evaluate the effectiveness of the dynamic EE algorithm in the presence of different types of background noise (stationary and non-stationary) at both the source and listener locations with different SNR conditions. Key new results from this study include: (1) objective speech intelligibility predictors are developed and utilized for the assessment of the dynamic EE algorithm, (2) the dynamic EE algorithm is effective only in certain combinations of source and listener SNR conditions, (3) the incorporation of noise reduction algorithms can expand the range of SNRs over which the dynamic EE is effective. In conclusion, the dynamic EE algorithm can be considered for improving the speech intelligibility for children suspected with APD and individuals with ANSD in poor SNR conditions at the listener location. Results portrayed in this chapter can potentially guide the choice and activation of the dynamic EE algorithms in assistive hearing devices (e.g. RM applications). In the next chapter, the subjective and objective performance of the static EE for hearing aid applications will be examined and discussed.

# Chapter 4

# 4 Static Envelope Enhancement Algorithm

In the second chapter, the published data on the effectiveness of the static EE on phrase identification scores (consonants- vowels) in individuals with ANSD and SNHL was discussed. In this chapter, development and assessment of the static EE algorithm for typical hearing aid (HA) applications is investigated. Although the static EE was available as the "Deepen band modulation" feature in the Praat software (version 6.0.25, Institute of Phonetic Science, University of Amsterdam, Netherlands), the static EE development, debugging and testing was completed using MATLAB 2017a on a personal computer platform. It is also pertinent to point out that the realtime implementation of the static EE algorithm is out of scope for the present study. Hence, only the offline processing of the static EE was evaluated in this chapter.

As described in the second chapter in Section 2.2, the benefit of the static EE for speech perception in patients with ANSD and SNHL has been demonstrated only for phrase recognition tasks. In addition, in the previous research work (e.g. [26] and [27]), the performance of the static EE has been evaluated by using the 'Deepen band modulation' feature in the Praat software. Furthermore, in the previous research work, the effectiveness of the static EE was only considered for the ideal condition of RM application, wherein the speech signal picked up by the microphone was assumed to be relatively clean, and the background noise was only added after enhancing the speech envelope. Hence, in the present study, the static EE was developed on a personal computer platform using MATLAB 2017, and the static EE was evaluated for the sentence-level speech perception by children with APD across different processing conditions. The aim of this study, therefore, is to investigate the performance of the static EE algorithm in enhancing speech perception by children with APD, in different types and levels of background noise. The following specific objectives will be examined in detail in this chapter (a) the effectiveness of the static EE algorithm for children with APD in hearing aid applications, (b) the potential benefit of applying different noise reduction algorithms as a front-end to the static EE, and (c) developing an objective speech intelligibility estimator to predict the perceptual impact of the static EE.

## 4.1 Implementation of static EE

### 4.1.1 Praat software (Deepen band modulation)

As mentioned earlier, the static EE was recently evaluated by Shetty and Kooknoor [27] based on the 'Deepen band modulation' feature in the Praat software by processing the input speech signal in critical bands. Figure 4-1 illustrates the graphical user interface (GUI) , where the enhancement, which indicates the maximum increase in the level is set to 20 dB; the lowest and highest frequencies that should be enhanced are set to 100 and 8000 Hz respectively; the slow and fast modulation rates, which indicate the modulated frequency range, are set to 3 and 30 Hz respectively; and the band smoothing, which determines the degree of overlap of each band into its adjacent bands, is set to 100 Hz.

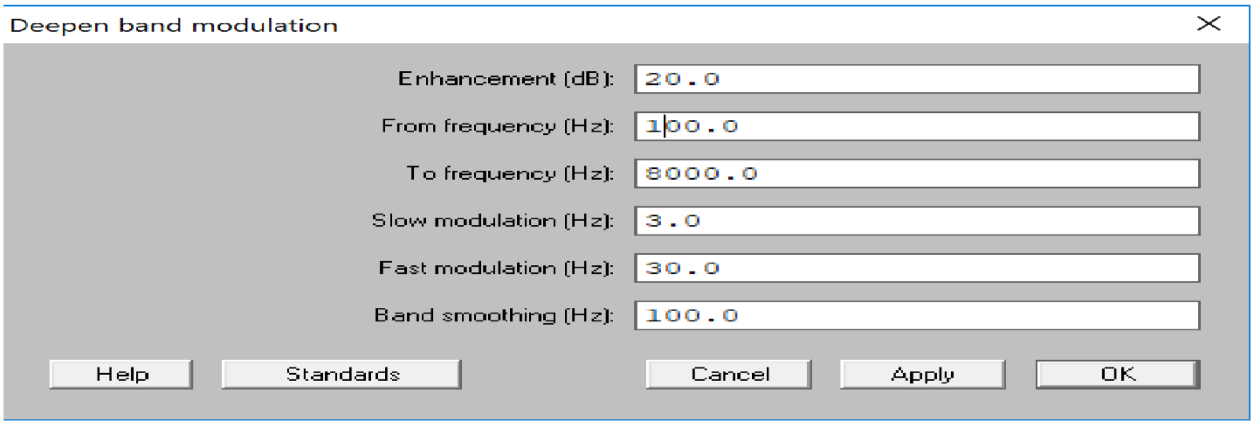



**Figure 4-1: GUI for Deepen band modulation feature in Praat software.**

### 4.1.2 MATLAB implementation

The static EE algorithm was implemented in MATLAB 2017a based on the algorithm that is available in Praat software. Figure 4-2 depicts the block diagram of the static EE algorithm.

As it can be seen from Figure 4-2, the processing of the static EE is conducted in both temporal and spectral domains, unlike the dynamic EE in which the whole processing is conducted in the temporal domain. The input speech signal, $x(n)$ is first converted to the spectral domain by applying fast Fourier transform (FFT). Then, the signal spectrum between 100 – 8000 Hz is segmented into 22 critical bands, with each band spanning one Bark. The transformation between the frequency ($f$) in Hz and the Bark scale ($b$) is shown in Equation 4.1.

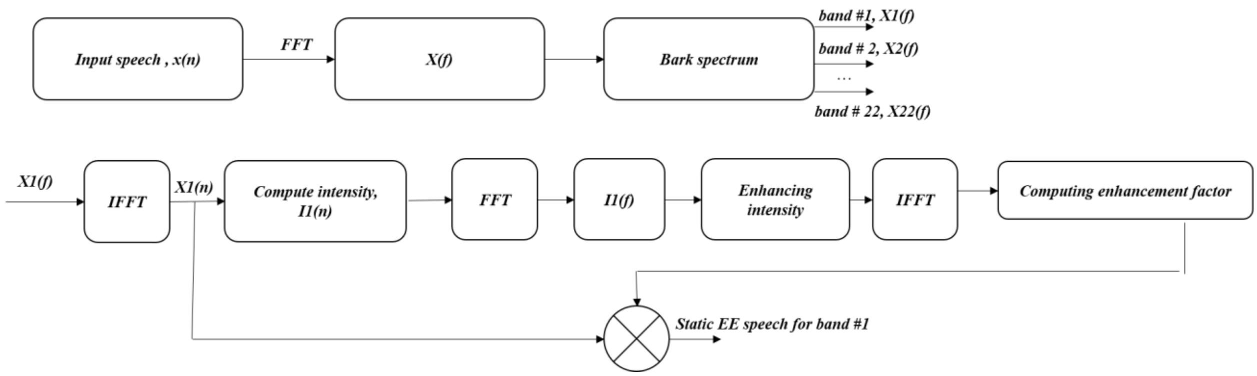



**Figure 4-2: Block diagram of the static EE algorithm.**

$$b = 7 * sinh^{-1}\left(\frac{f}{650}\right) + 1 \tag{4.1}$$

The next stage is to convert the spectrum bands into temporal domain by taking the inverse fast Fourier transform (IFFT). Then, the intensity for each Bark band is computed as shown in Equation 4.2.

$$i(n) = 10 * log_{10}(x^2(n) + 10^{-6}) \tag{4.2}$$

Then, the computed intensity in each band is converted to the spectral domain by applying FFT to the intensity in the time domain. After that, the intensity for each Bark band is enhanced by multiplying with the transfer function of a band pass filter (*H(f)*), which is shown in Equation 4.3, where $\alpha = \sqrt{ln2}$ , $f_{slow}$ = 3 Hz, and $f_{fast}$ = 30 Hz

$$H(f) = e^{(-(\frac{\alpha f}{f_{fast}})^2)} - e^{(-(\frac{\alpha f}{f_{slow}})^2)} \tag{4.3}$$

After that, the enhanced intensity ($i_{enh}$) in each Bark band is converted to the temporal domain by applying IFFT.

Then, the enhancement factor, which is computed from Equation 4.4, is multiplied with the original signal in each Bark band in the temporal domain. Finally, the enhanced signals in each Bark band are added together to generate the static EE output speech signal. It is pertinent to point out that Figure 4-2 only shows the processing stages for the first Bark band. However, the similar procedure is conducted for the remaining Bark bands.

$$enhancement = 1 + (10^{\frac{enhancement}{20}} - 1) \cdot (0.5 - 0.5 * cos(\frac{\pi f_{midbark}}{13})) \tag{4.4}$$

It should be noted that the enhancement is fixed at 20 dB, and $f_{midbark}$ is defined as the middle frequency of the band.

Figure 4-3 shows the static EE of a sample stimulus processed by Praat software and MATLAB. It can be noted from this figure that the MATLAB implementation of the static EE is identical to its Praat version.

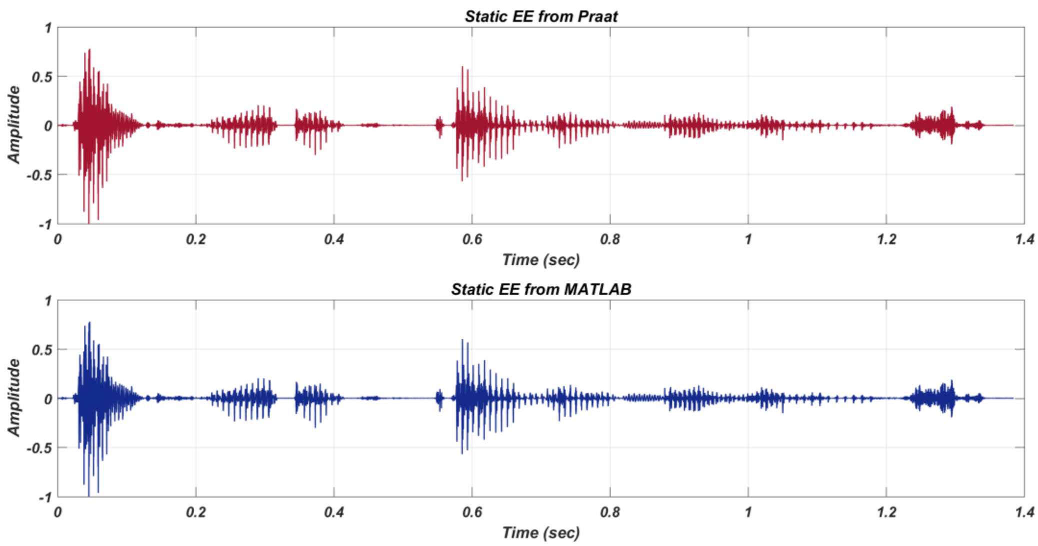



**Figure 4-3: Comparison of the generated static EE stimulus from Praat and MATLAB.**

### 4.1.3 Modulation spectrogram analysis

The distribution of modulation energy as a function of modulation frequency and acoustic frequency, which is averaged over all speech frames, was determined for both clean speech and static EE speech in MATLAB. Figure 4 – 4 allows for visualization of the impact of the static EE algorithm. It can be observed from Figure 4 – 4 b that the static EE boosts the modulation energy significantly in 4 – 10 Hz only for acoustic channels around 1000 Hz. As mentioned earlier, it is well-known that slow temporal envelope modulations in the 4 – 10 Hz provide useful cues for speech perception [4]. It is evident from Figure 4 – 4 b that the static EE algorithm exaggerates these useful cues.

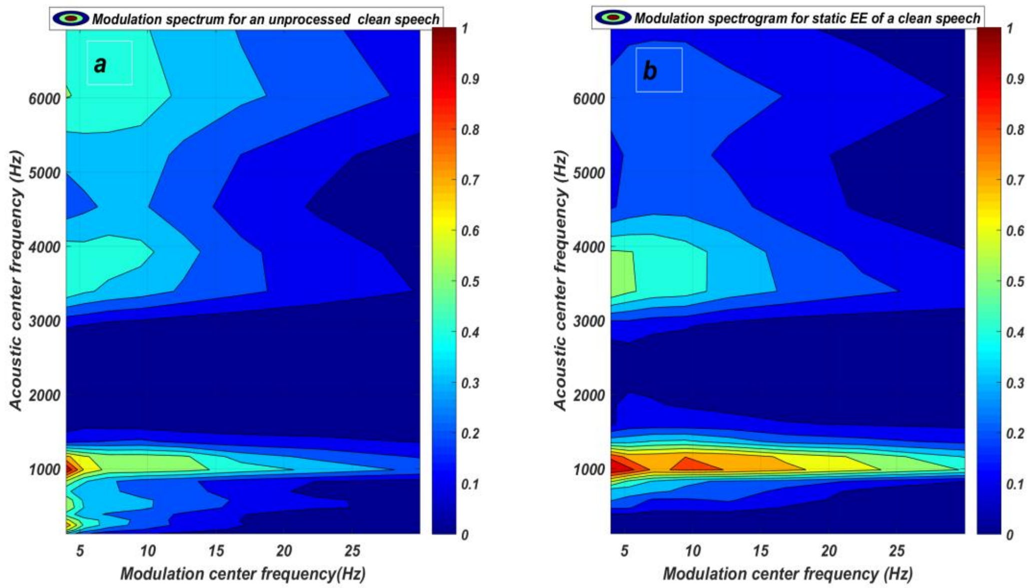



**Figure 4-4: Modulation spectrograms for the original and enhanced speech sample. (a) original speech, (b) static EE.**

## 4.2 Subjective assessment procedure

### 4.2.1 Database

A noisy speech database was created for the subjective and objective assessment of the speech intelligibility in a manner similar to Chapter 3, wherein the clean speech sentences were taken from the Hearing in Noise Test (HINT) database [28]. The clean speech sentences were corrupted by two different types of noise, stationary (HINT speech-shaped-noise (SSN)) and non-stationary (multi-talker-babble-noise (MTBN)) at four different SNRs. The noisy speech stimuli were then processed by static EE. In addition, in order to assess the benefits of incorporating a NR algorithm as a front-end to the static EE, logMMSE and MHA NR algorithms were applied to the noisy speech prior to the application of the static EE algorithm. Thus, the database contained 25 lists x 10 sentences/list x 2 types of background noise (SSN and MTBN) x 4 SNRs (3 dB, 0 dB, -3 dB, and -6 dB) x 4 processing conditions (unprocessed, SEE, logMMSE&SEE, and MHA&SEE) = 8000 stimuli.

### 4.2.2 Audio presentation and speech intelligibility measurement

Speech perception in noise was measured in a manner similar to the method discussed in Chapter 3 (viz. speech stimuli were played via the interface shown in Figure 3-7). As discussed in Chapter 3, the participants received the signal diotically through a pair of Sennheiser HDA 200 headphones at the most comfortable level. In addition, participants were told that they would hear sentences in background noise, and they heard each sentence just one time. The participants had to repeat the speech token heard by them, and the number of correctly repeated key words were logged before presenting the next sentence in the list. It is also important to note that the order of processing conditions was randomized and counterbalanced across the participants.

### 4.2.3 Participants

Subjective data collection was performed in two experiments: stationary background noise and non-stationary background noise. In the stationary background noise experiment, the static EE algorithm was evaluated subjectively in the presence of SSN by two different groups of participants: ten children with APD, and ten children with normal hearing. The children with APD and NH ranged between 8.1-13.5 and 8.4-17.4 years respectively. For the non-stationary background noise experiment, the MTBN background noise database was utilized for benchmarking the performance of the static EE at different SNRs. Then, the performance of the static EE was evaluated subjectively by a new APD group of ten participants, who were distinct from the APD group that participated in the stationary background noise experiment. It should be noted that the children with APD participating in the non-stationary background noise experiment ranged between 7.9 – 15 years in age.  It is pertinent to point out that children suspected of APD were referred to H.A. Leeper Speech and Hearing clinic at Western University because their parents or teachers expressed concerns about their listening abilities. Case history, behavioral surveys, questionnaires of auditory processing problems , educational risk and screening identification for targeting educational risk indicated that these children were at risk and should undergo auditory processing assessment [72]. The auditory processing assessment was carried out on children suspected of APD and children were identified as APD based on ASHA guidelines [64]. Children with NH had no developmental or academic or listening concern. All participants hearing thresholds were within 25 dB HL at octave frequencies from 250- 8000 Hz. One APD child’s hearing threshold at 8000 Hz was 30 dB HL in the left ear.

## 4.3 Subjective analysis

### 4.3.1 Stationary background noise experiment

#### 4.3.1.1 Averaged ratings (plots)

The averaged speech intelligibility scores along with their standard deviation for the APD and children with normal hearing participant groups are illustrated in Figure 4 - 5 and Figure 4 - 6 respectively, where the UP, SEE, logMMSESEE, and MHASEE conditions represent (1) the unprocessed, (2) static EE by itself, (3) combination of logMMSE NR and static EE, and (4) combination of MHA NR and static EE of noisy speech at different SNR values respectively. The subjective results in Figure 4 – 5 demonstrate that for the APD participant group, SEE was better in terms of the speech intelligibility mean scores only for SNR = -3 dB compared to UP condition. On the other hand, as illustrated in Figure 4 – 6, for the children with normal hearing participant group, SEE was worse in terms of the speech intelligibility mean scores compared to UP regardless of the SNR parameter. The results also demonstrate that the incorporating of MHA NR algorithm as a front-end to the static EE results improved the effectiveness of the static EE only for poorest SNR (i.e. SNR = -6 dB) across participant groups. However, as can be noted from Figures 4 – 5 and 4 – 6, the application of logMMSE NR algorithm can be seen to be inferior compared to MHA NR algorithm irrespective of the SNR values and participant groups.

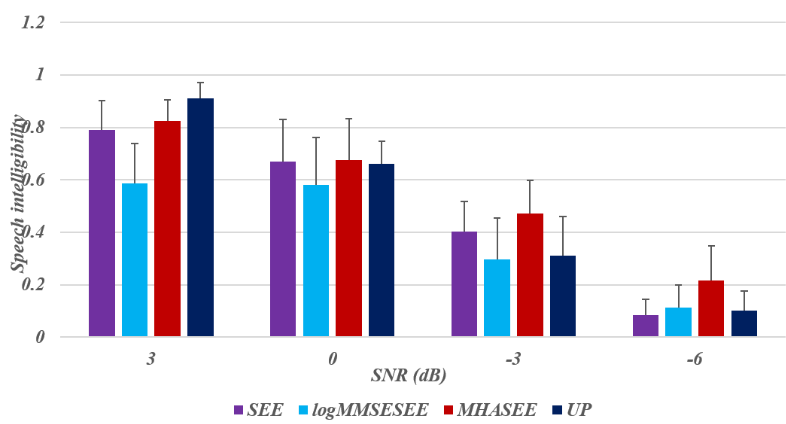



**Figure 4-5: Averaged speech intelligibility scores for children with APD.**

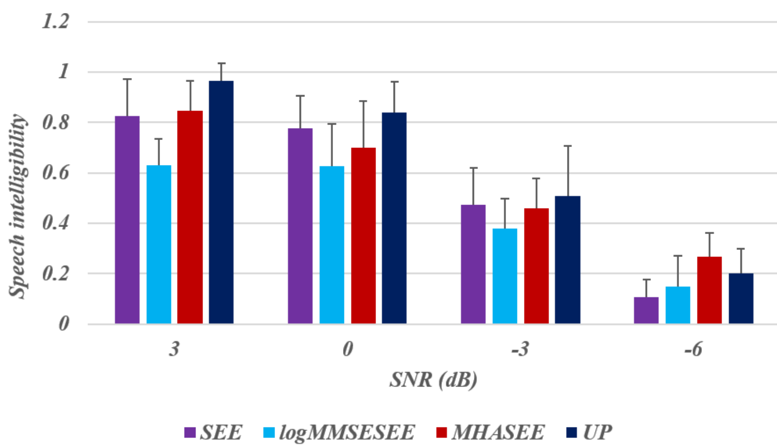



**Figure 4-6: Averaged speech intelligibility scores for children with NH.**

### 4.3.1.2 Statistical analysis

Repeated measures ANOVA was conducted with the results obtained from the children with normal hearing and children with APD participant groups to determine whether these differences were statistically significant. In a manner similar to Chapter 3, the raw scores were first transformed to RAUs by using Equation 3.3, and the repeated measures ANOVA was performed with different processing (i.e. UP, SEE, logMMSESEE, and MHASEE) and SNR as the within-subject factors. Mauchly's test of sphericity was not violated for any of the variables. There were significant main effects of processing ($F(3, 54) = 30.322$, $p < 0.001$) and SNR ($F(3, 54) = 422.722$, $p < 0.001$) parameters. There was no statistically significant interaction between the processing, SNR parameters and the subjective groups (normal vs. APD), indicating that altering the processing and SNR values had a similar effect across both participant groups. However, there was significant interaction between processing and SNR variables ($F(9, 162) = 12.928$, $p < 0.001$), suggesting that the relative performance of the static EE algorithm for a given condition depended on the SNR parameter.

To further investigate this interaction, post-hoc comparisons between subjective data at different processing and SNR values were conducted with Bonferroni correction. The first salient outcome of this analysis showed that the scores associated with MHASEE processing were significantly better than UP, SEE, and logMMSESEE scores only at SNR = -6 dB. In addition, the performance of MHASEE condition was statistically better than logMMSESEE at SNRs 3 and -3 dB, while the performance of these two conditions was statistically similar only at SNR = 0 dB. The second salient outcome of this analysis indicated that the performance of SEE and logMMSE processing was statistically similar at SNRs -3 and -6 dB, while SEE condition is statistically better than logMMSESEE at SNRs 3 and 0 dB. In addition, the performance of SEE and MHASEE processing was statistically similar for all SNRs values except for SNR = -6. The last salient outcome of this analysis illustrated that the scores associated with SEE condition were significantly poorer than unprocessed scores only at SNR = 3 dB, while the performance of SEE and UP processing was statistically similar at SNRs 0, -3, and -6 dB.

## 4.4 Non-stationary background noise experiment

### 4.4.1 Averaged ratings (plots)

The averaged speech intelligibility scores for the new group of children with APD along with their standard deviations are illustrated in Figure 4 – 7. The subjective results shown in Figure 4 – 7 demonstrate that the application of the static EE by itself, and the incorporation of NR algorithms as a front-end to the static EE was inferior in improving speech intelligibility irrespective of the SNR values when the background noise was non-stationary (MTBN).

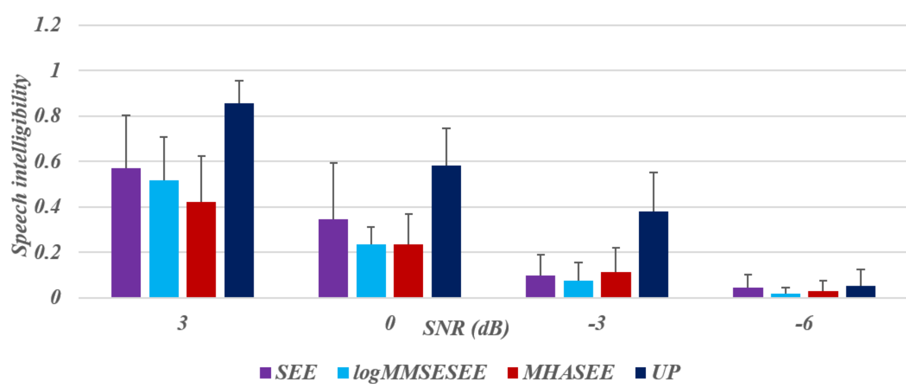



**Figure 4-7: Averaged speech intelligibility scores for children with APD.**

A separate statistical analysis was conducted with the results obtained from the children with APD in a manner similar to the stationary background noise experiment. The repeated measures ANOVA was performed with SNR and processing (UP, SEE, logMMSESEE, and MHASEE) as the within-subject factors. Mauchly's test of sphericity was violated for the condition variable ($\chi^2(5) = 11.774$, $p = 0.039$), so the Greenhouse- Geisser correction was used for this condition ($\varepsilon = 0.548$). There were significant main effects of SNR ($F(3, 27) = 77.717$, $p < 0.001$) and condition ($F(1.645, 14.807) = 142.220$, $p < 0.001$) parameters. In addition, there was a significant interaction between the SNR and condition variables (F

(3.492, 31.432) = 8.034, $p < 0.001$), indicating that the relative performance of the static EE algorithm for a given condition depended upon the SNR value.

To further investigate this interaction, post-hoc comparisons between the subjective data at different SNR and processing values were conducted with Bonferroni correction. Major outcomes of this analysis include: (1) the UP scores were significantly better than the ones associated with SEE, logMMSESEE, and MHASEE processing for all SNR values, except for SNR = 0, where the scores from SEE processing was statistically similar to UP scores, (2) the performance of the SEE processing was statistically better than logMMSESEE and MHASEE conditions regardless of SNR values; and (3) the performance of logMMSESEE was statistically better than MHASEE only at SNR = 3 dB, while for the other SNR values, the scores associated with logMMSESEE was statistically similar to MHA processing. It should be noted that the SPSS outputs from both stationary and non-stationary background noise experiments can be found in Appendix C of this thesis.

## 4.5 Objective analysis

### 4.5.1 Stationary background noise experiment

#### 4.5.1.1 First phase

In the first phase of the objective assessment, both HASPI and ModA objective indices were applied to predict the speech intelligibility for static EE algorithm across the same processing conditions applied during the subjective assessment of the stationary background noise experiment. As it was mentioned in Chapter 3, the computation of HASPI and ModA were based on the MATLAB code provided by Kates [30] and Chen et al [31]. Correlation coefficients and standard errors of estimation were used for evaluating the performance of these two objective metrics (i.e. HASPI and ModA). A correlation analysis was employed in such a way that, objective scores were computed for each processing conditions across all individual APD subjective scores (i.e. total 160 scores, ten APD subjects x 16 processing conditions [4 processing (SEE, logMMSESEE, MHASEE, and UP) x 4 SNRs (3, 0, -3, and -6 dB)]. Hence, 160 pairs of subjective and objective scores were available for correlation analysis. It is pertinent to point out that a list of ten sentences was randomly selected from the SSN database for each processing condition, and the objective speech intelligibility predictors (HSPI and ModA) were computed from all ten sentences in the list. Therefore, the average HASPI and ModA objective scores across these ten sentences were correlated with their corresponding subjective scores.

**Table 4-1: Correlation coefficient and standard error of estimation for HASPI and ModA.**

| Objective measure | $\rho$ | $\sigma_e$ |
|---|---|---|
| HASPI | 0.75 | 0.19 |
| ModA | 0.24 | 0.28 |

Table 4.1 shows the correlation coefficients and the standard errors of estimation for HASPI and ModA metrics. It can be noted from Table 4.1 that HASPI exhibited significantly higher correlation with the subjective scores compared to ModA. In addition, HASPI shows less percentage standard error of estimation compared to ModA. Figure 4 – 8 depicts the scatter plot of the predicted values of the speech intelligibility scores from HASPI and ModA versus the actual APD subjective scores. It can be noted from Figure 4 – 8 that the majority of HASPI scores are located close to the line of identity (equality) unlike the ModA scores, which are located far from the line of identity.

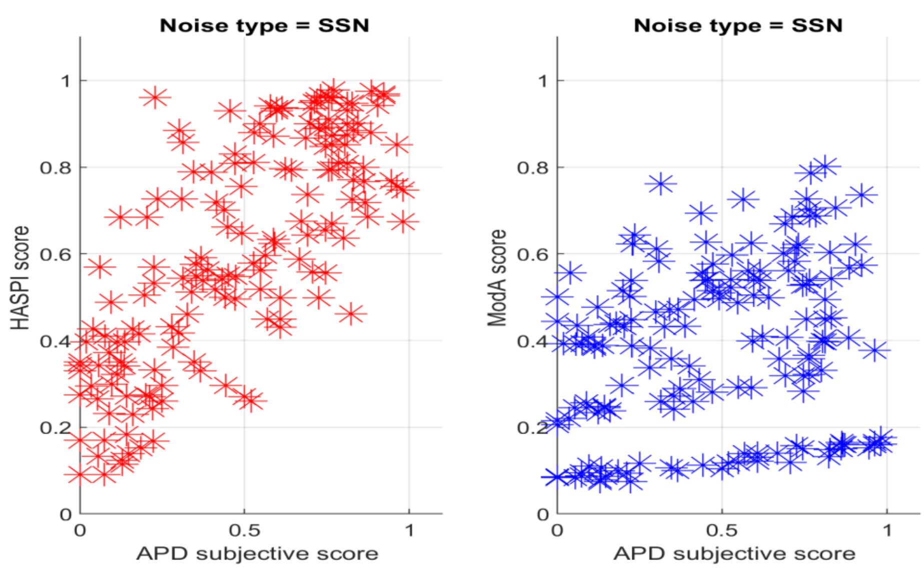



**Figure 4-8: Scatter plot of the predicted and APD subjective scores for HASPI and ModA.**

### 4.5.1.2 Second phase

Since HASPI correlated highly with the APD subjective scores for the stationary background noise experiment, it can be used to evaluate the performance of static EE algorithm for non-stationary background noise experiment. However, to find a better mapping between HASPI and subjective data, a data-driven approach was taken to derive an objective predictor in a similar manner of dynamic EE. As it was discussed in Chapter 2, section 2.6.1, HASPI scores are computed from the raw features of HASPI [i.e. cepstral correlation (c) and three-level temporal fine structure covariances ($a_{Low}$, $a_{Mid}$, and $a_{High}$) as shown in Equation 2.1]. Hence, in the second phase of the objective assessment, a modified HASPI metric was derived by computing the raw features of HASPI for each individual subjective score across each processing condition [viz. 160 scores (ten APD subjects x 16 processing conditions)]. Then, various multivariate regression analyses were performed between HASPI features and APD subjective data to derive an objective speech intelligibility predictor.

#### 4.5.1.3 Training the model

Multivariate regression analysis was conducted by applying machine learning techniques via 'Regression Learner 'feature in MATLAB. It should be noted that automated training was performed to search for the best regression model type, the one that achieves the lowest value of root mean square error (RMSE). The HASPI features (viz. C, $a_{Low}$, $a_{Mid}$, and $a_{High}$) and the APD subjective scores from the stationary background noise experiment were defined as predictors and response variables respectively to the regression model. After training a model in 'Regression Learner' application in MATLAB, an objective predictor was derived as a combination of a set of HASPI features following the same procedure that was conducted by Kates [5]. The best predicted model that can explain the highest amount of variance (79%) and the lowest value of RMSE (0.1318) was found to be a regression tree model. It should be noted that the regression tree model is termed as 'static EE data trained (SEEDT)' model for the rest of this thesis.

#### 4.5.1.4 Testing SEEDT model

In order to assess the accuracy of SEEDT model, the correlation analysis was performed to measure the strength of a relationship between the predicted subjective scores from the SEEDT model and subjective scores, followed by computing the standard error of estimation and Bland-Altman analysis to evaluate the reliability of the SEEDT model. The correlation analysis was performed across the subjective data and their corresponding predicted subjective scores form the model in a manner similar to section 4.4.1.1. In fact, predicted subjective scores are computed by applying SEEDT model to the raw-features of HASPI computed for stationary and non-stationary background noise database. Hence, 160 pairs of subjective and predicted subjective scores were available for each correlation analysis (e.g. NHC and children with APD participants).

It can be noted from Table 4.2 and Fig 4-9 that the SEEDT model exhibited the stronger relationship with NHC subjective scores, which were collected from the stationary background noise experiment, compared to APD subjective scores, which were collected from the non-stationary background noise experiment. In addition, the predicted subjective scores showed a lower standard error of estimation for NHC compared to APD participants. The Bland-Altman plots associated with NHC and APD subjective scores are displayed in Figs 4 –10 and 4 – 11 respectively. It should be noted from Figs 4 – 10 and 4 – 11 that the mean difference scores were 0 % and - 27.68 % for NHC and APD subjective scores respectively. Hence, it can be noted that the model is significantly more reliable in predicting NHC subjective scores for the stationary background noise experiment compared to predicted APD subjective scores for the non-stationary background noise. As it was mentioned in Chapter 3, a mean difference score that differs from zero is evidence of bias in the model, while a zero-mean difference score indicates a perfect agreement between the actual and predicted subjective scores. Therefore, the amount of bias in the model, which is relative to the measurement error, is significantly higher for APD subjective scores compared to NHC subjective scores.

Table 4.2 Correlation coefficient and standard error of estimation for NHC and children with APD

**Table 4-2: Correlation coefficient and standard error of estimation for NHC and children with APD.**

| Predicted subjective scores | $\rho$ | $\sigma_e$ |
|---|---|---|
| NHC | 0.94 | 0.09 |
| Children with APD | 0.77 | 0.18 |

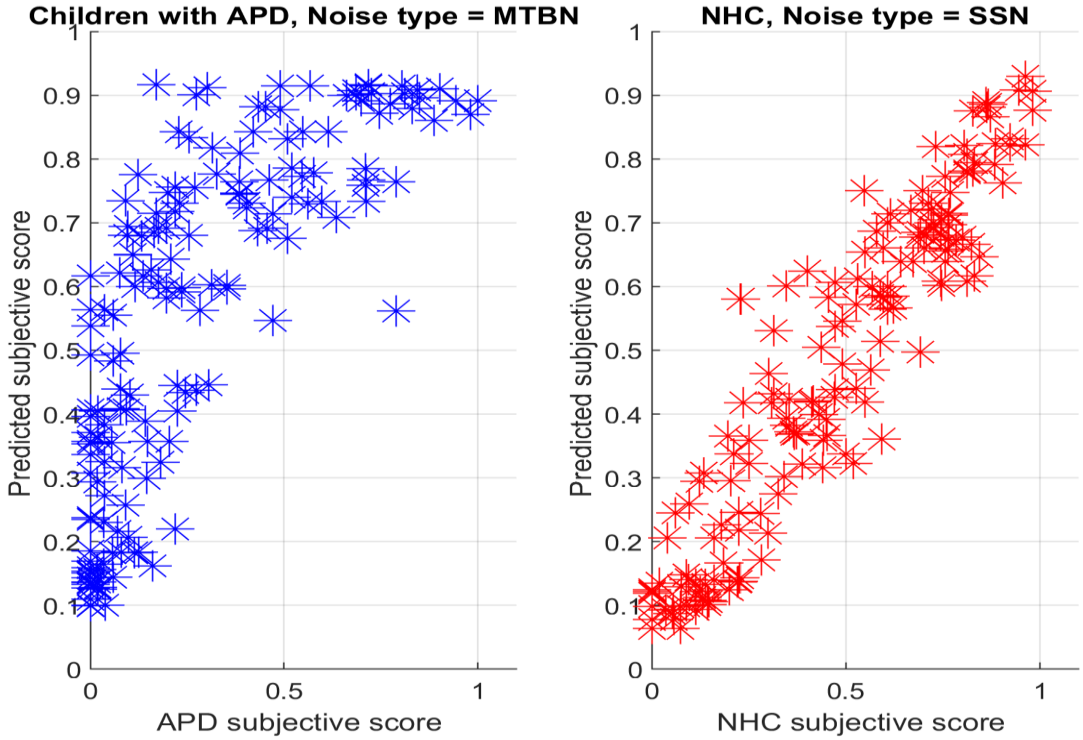



**Figure 4-9: Scatter plot of the predicted and actual subjective scores for children with APD and NHC.**

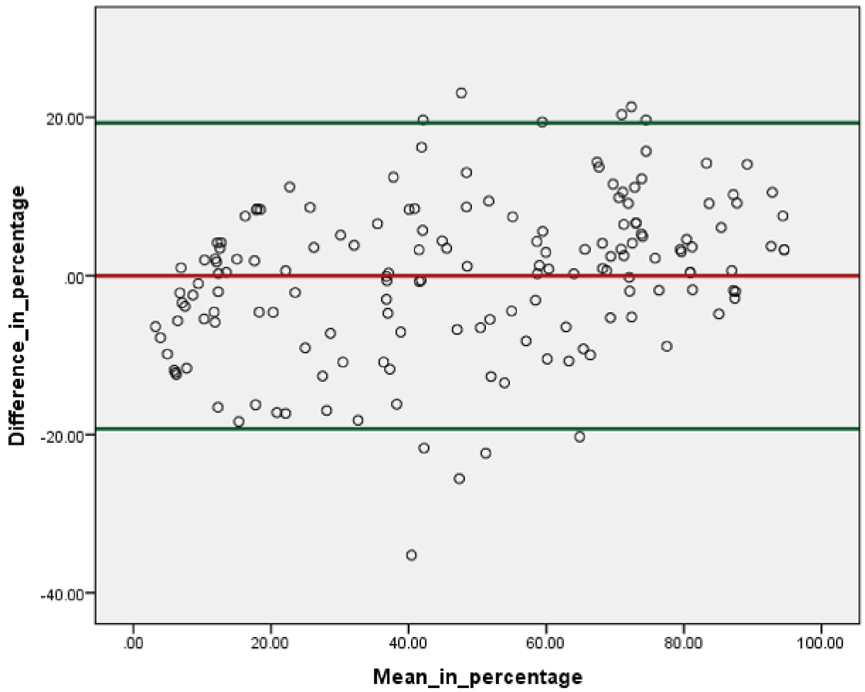



**Figure 4-10: Bland-Altman plot (NHC subjective scores versus predicted scores).**

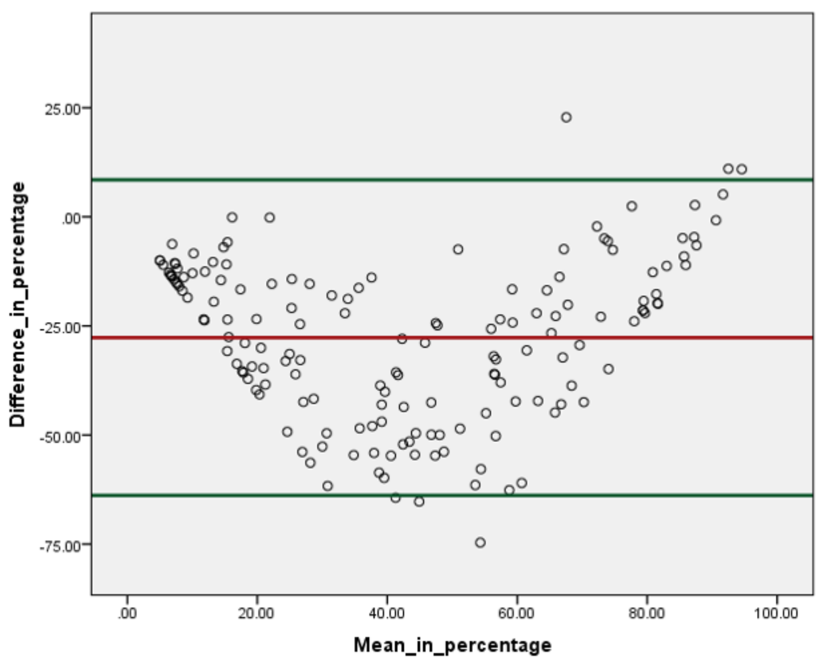



**Figure 4-11: Bland-Altman plot (APD subjective scores versus predicted scores).**

## 4.6 Discussion

This chapter contributed novel experimental results on the benefits of the static EE when the enhancement was applied to the noisy speech at different SNRs in the presence of stationary and non-stationary background noise for children with auditory processing disorder. Furthermore, an objective model was derived to predict the speech perception for further benchmarking of the static EE in different processing conditions (e.g. RM applications of the static EE). These salient experimental results are discussed in the following sections:

### 4.6.1 Subjective and objective data

To the best of our knowledge, this study is the first one to show that children with APD do benefit from static EE. In addition, this study is the first one to show the effectiveness of the static EE for hearing aid applications with this population.

This chapter also explored two objective metrics, (viz. HASPI and ModA), as they have been previously validated with speech perception data from hearing impaired listeners and cochlear implant subjects. Our experimental results showed that HASPI had a significantly better correlation with subjective scores from children with APD compared to ModA. However, since in real-time signal processing applications achieving a reference speech (clean speech) is a challenging task, proposing a non-intrusive objective metrics (e.g. ModA) is preferred. Therefore, in the next chapter of the thesis, a novel objective predictor will be proposed to predict the perceptual impact of new EE algorithms by training a model based on APD subjective scores, which were collected from both stationary and non-stationary background noise experiments, and ModA features.

Although the raw correlation between HASPI and subjective scores in the stationary background noise study was high (0.82), a multivariate tree regression model (i.e. SEEDT) was derived to better describe the relationship between HASPI raw features [envelope cepstral correlation (C), Low-level($a_{Low}$), Mid-level($a_{Mid}$), and High-level ($a_{High}$) fine structure)] and the subjective scores. This approach is novel to the static EE algorithm assessment, but as it was mentioned in Chapter 3, the same strategy has been employed before for evaluating hearing aid algorithms such as the research study conducted by Kates [70] to assess single microphone noise reduction algorithm objectively.

### 4.6.2 Static EE, and interaction with noise type and SNR

This chapter benchmarked the performance of the static EE for hearing aid applications at different SNRs and noise types. The results suggested that incorporating the static EE by itself was inferior in improving the speech intelligibility scores regardless of the SNR values and background noise type across participant groups. In general, it can be observed from the experimental results that the performance of the static EE algorithm depends upon the SNR parameter and type of the background noise. These critical parameters were not explored comprehensively in previous research [26] and [27].

### 4.6.3 Effect of the NR algorithm

As the performance of the static EE was not statistically better in terms of the speech intelligibility compared to unprocessed condition when the enhancement was applied to the noisy speech instead of clean speech, it is potentially beneficial to consider noise mitigation prior to SEE. Hence, a NR reduction algorithm as a front-end to envelope enhancement algorithm may improve the effectiveness of the SEE when the SNR is poor. Kuk [20] showed that children with APD performed better with directional microphone processing and NR. This chapter employed a well-known NR algorithm, the logMMSE as well as the MHA NR algorithm to reduce the noise prior to SEE. Statistical results demonstrate that the performance of the MHA NR was superior compared to its counterpart, logMMSE NR algorithm when the background noise is stationary at poor SNRs (e.g. SNR = -3 and SNR = -6 dB). However, the performance of both the logMMSE and MHA NR algorithms is inferior when the background noise is non-stationary regardless of the SNR values due to the fact that NR algorithms work best with stationary noise sources [59]. Statistical results also demonstrate that the application of logMMSE NR prior to the application of the static EE was not beneficial to improve the effectiveness of the static EE performance regardless of the processing condition. On the other hand, incorporating MHA NR algorithm as a front-end to the static EE improves the performance of the static EE when the background noise is stationary only for SNR = -6 dB. It is important to note that for the stationary background noise, the MHA NR performed better compared to its rival since MHA NR applies a much more efficient method to smooth the maximum likelihood estimate of the SNR compared to logMMSE NR.

### 4.6.4 Robustness of SEEDT model

In this study, we derived an objective predictor (SEEDT) by training the APD subjective data, which were collected from the stationary background noise experiment. Since, there is a noticeable difference in model features between stationary and non-stationary background noise experiments, the SEEDT model exhibited significantly more robustness when it was tested with NHC subjective data, which were collected from the stationary background noise experiment compared to when it was tested with APD subjective data, which were collected form the non-stationary background noise experiment. Therefore, a generalized model that can predict the perceptual impact of the static EE algorithm with the highest degree of correlation and reliability for both stationary and non-stationary background noise environments is essential, which is discussed and evaluated in more details in the next chapter.

Generally, the experimental results presented in this chapter are worthwhile in developing initial recommendations on when the static EE algorithm can be expected to be beneficial in hearing aid device applications. It is evident from the results that the only benefit from static EE is accrued when the SNR is poor (e.g. SNR = -6), the MHA NR is incorporated as a front-end to the static EE, and the background noise is stationary. Thus the decision to activate the static EE algorithm can be driven by the automatic environment classification algorithms in modern hearing aids, which estimate the type and level of the background noise.

## 4.7 Summary

This chapter portrayed the performance of static EE for hearing aid applications by conducting both subjective and objective experiments. The first study evaluated the impact of static envelope enhancement on speech intelligibility subjectively and objectively, in the presence of the stationary background noise and when the static enhancement was applied to the noisy speech at different SNRs. In the non-stationary background noise experiment, the subjective and objective experiments were conducted to evaluate the effectiveness of the static EE in the presence of a non-stationary background noise at the same processing conditions as well as evaluating the objective predictors with the subjective data collected from both stationary and non-stationary background noise experiments. Novel results from this study include the following : (a) the static EE by itself is not beneficial in improving the speech intelligibility regardless of the subjective group and processing conditions, (b) the incorporating of the MHA NR algorithm is beneficial only for the poorest SNR condition when the background noise is stationary, while the application of the logMMSE NR algorithm prior to the static EE is not beneficial regardless of the noise type and processing condition, and (c) objective speech intelligibility predictor is developed from the assessment of static EE algorithm, which can potentially be used for benchmarking new EE algorithms. Demonstrated results in this chapter can potentially guide the choice and activation of the static EE in assistive hearing device applications (e.g. hearing aid applications). In the next chapter, first, the robustness of individually trained models (i.e. DEEDT and SEEDT) will be evaluated by exhibiting how well the DEEDT and SEEDT models predict subjective data from static and dynamic EE experiments respectively.

Second, a generalized form of trained models based on HASPI and ModA features will be trained and tested with companding algorithm.

# Chapter 5

# 5 Speech intelligibility prediction models for EE algorithms

In the third and fourth chapters, individual models (DEEDT and SEEDT) were derived by training APD subjective scores and their corresponding HASPI features in the presence of stationary background noise. The robustness of the DEEDT model was evaluated by testing this model with the subjective data, which were collected from children and adults with normal hearing, who participated in dynamic EE evaluation. In addition, the robustness of SEEDT model was evaluated by testing the model with the subjective data, which were collected from children with normal hearing, who participated in non-stationary background noise experiment of the static EE evaluation. In this chapter, the robustness of DEEDT and SEEDT models will be evaluated by testing these models with APD subjective scores, which were collected from both static and dynamic EE evaluations respectively (i.e. testing DEEDT and SEEDT with APD subjective scores, which were collected from static and dynamic EE evaluations, respectively). In addition, generalized models will be derived by using all the APD subjective scores, which were collected from both dynamic EE and static EE, and their corresponding HASPI and ModA features. Furthermore, an optimal speech intelligibility prediction model is proposed for assessment and evaluation of new EE algorithms. Finally, the implementation of companding algorithm will be examined, and the effectiveness of the companding algorithm will be evaluated objectively by using the derived prediction model.

The following specific objectives will be examined in detail in this chapter (a) testing the robustness of DEEDT and SEEDT models in predicting the speech intelligibility scores from children with APD, which were collected from static EE and dynamic EE experiments, (b) developing a non-intrusive objective model that can predict APD subjective scores extracted from novel EE algorithms, and (c) evaluating the companding algorithm in different noisy conditions by employing the proposed objective speech intelligibility estimator to predict the perceptual impact of the companding algorithm.

## 5.1 Robustness of the individual EE models

### 5.1.1 DEEDT model

The robustness of the DEEDT model was evaluated in Chapter 3 by testing this model with subjective data, which were collected from both children and adult participants, who have normal hearing, in the presence of stationary background noise. In addition, in this section, the robustness of the model is tested with subjective scores, which were collected from children with APD, who participated in stationary and non-stationary evaluations of static EE. Scatter plots of predicted versus subjective scores for stationary and non-stationary background noise experiments can be seen in Figure 5-1, which shows the stationary background noise experiment has values scattered around the diagonal compared to the non-stationary background noise dataset. It can be seen from Table 5.1 that the DEEDT model shows slightly higher degree of correlation and lower standard error of estimation with the stationary background noise experiment compared to the non-stationary background noise experiment. Furthermore, the Bland-Altman plots for APD scores from SSN and MTBN experiments are displayed in Figures 5-2 and 5-3 respectively. It can be noted from these figures that the mean difference scores, which indicate an evidence of bias in the predictor, is more than three times lower for stationary background noise compared to non-stationary background noise. Hence, the DEEDT model is more reliable and accurate when it is applied to predict the subjective scores corresponding to the stationary background noise environment compared to predicting the subjective scores corresponding to the non-stationary background noise environment.

**Table 5-1: Estimated correlation coefficient and standard error of estimation for DEEDT model.**

| DEEDT predicted scores | $\rho$ | $\sigma$ |
|---|---|---|
| APD scores from SSN experiment of static EE evaluation | 0.82 | 0.16 |
| APD scores from MTBN experiment of static EE evaluation | 0.72 | 0.19 |

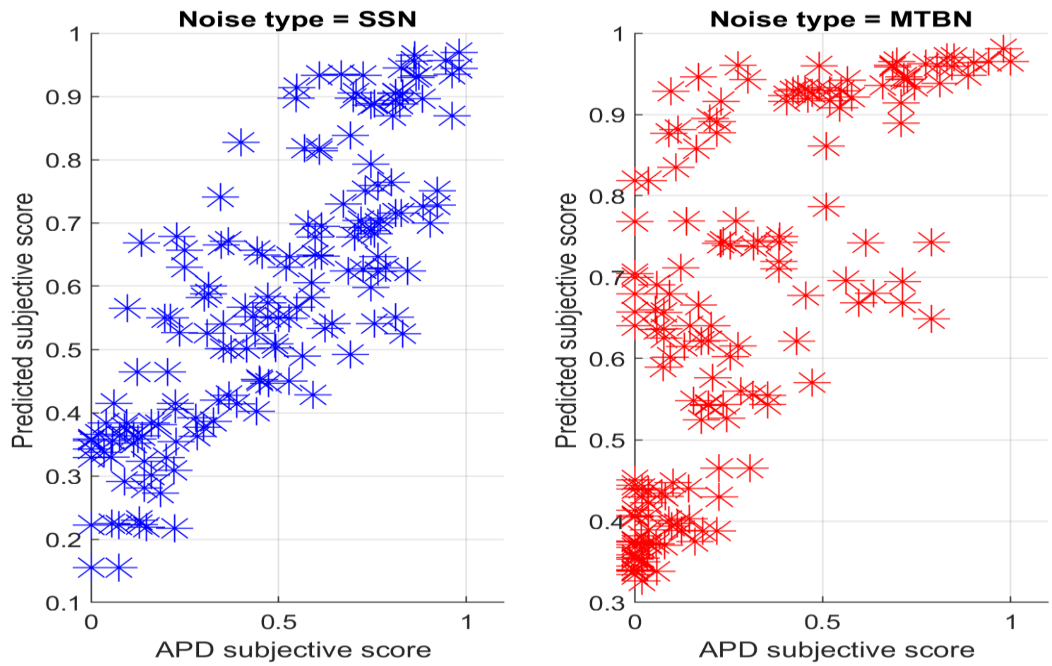



**Figure 5-1: Scatterplots showing the relationship between actual APD subjective scores and predicted scores for SSN and MTBN.**

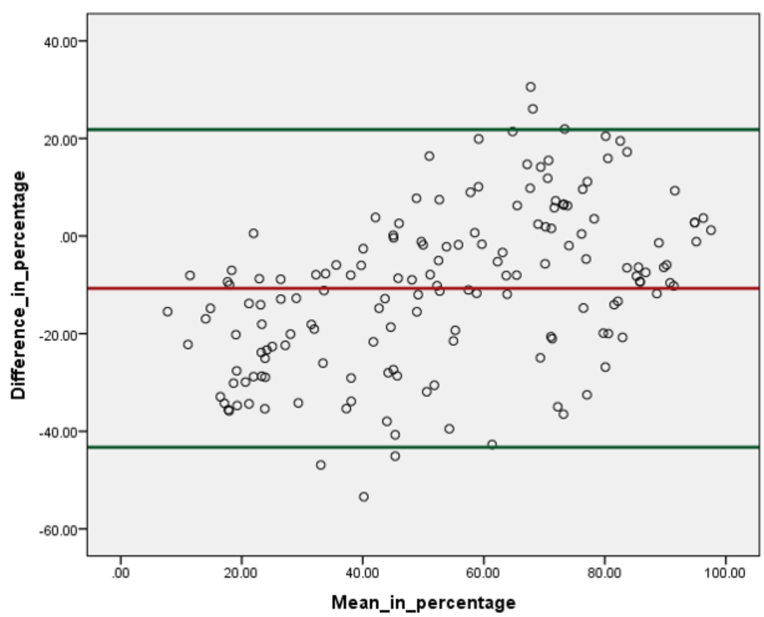



**Figure 5-2: Bland-Altman plot (APD subjective scores from SSN experiment versus predicted scores).**

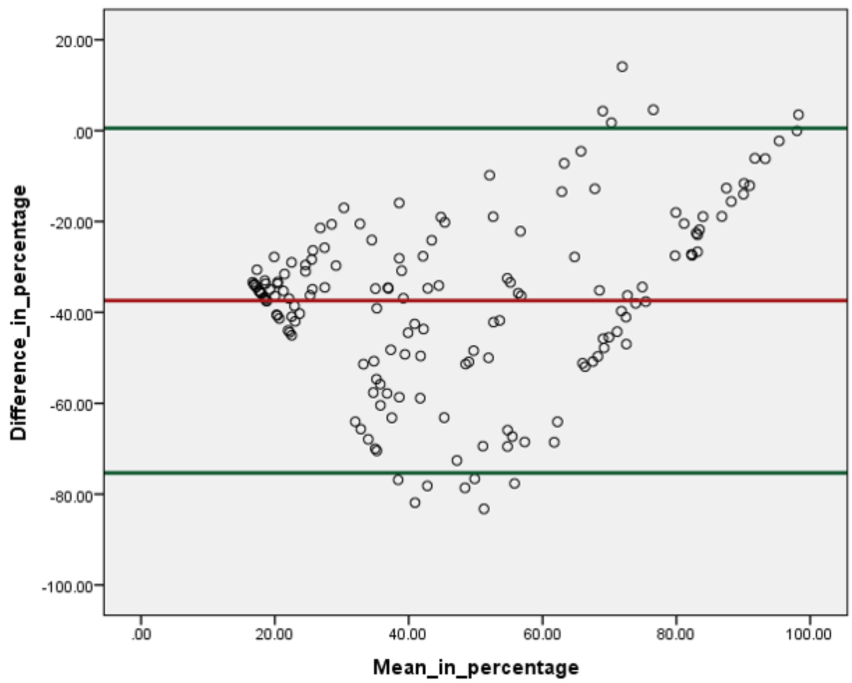



**Figure 5-3: Bland-Altman plot (APD subjective scores from MTBN experiment versus predicted scores).**

## 5.1.2 SEEDT model

The robustness of SEEDT model was evaluated in Chapter 4 by testing with both NHC and APD subjective scores, which were collected from the stationary and non-stationary background noise experiments , respectively. In addition, in this section, the robustness of the model is examined with APD subjective scores, which were collected from evaluating the dynamic EE in the presence of stationary background noise. The robustness of SEEDT model can be noted from Table 5.2, which shows the correlation coefficient and the standard error of estimation. In addition, the scatter plot of predicted scores versus subjective scores can be seen from Figure 5-4. Furthermore, the Bland-Altman plot that is shown in Figure 5-5 indicates the agreement between predicted and actual APD subjective scores.

**Table 5-2: Estimated correlation coefficient and standard error of estimation for SEEDT model.**

| SEEDT predicted scores | ρ | σ |
|---|---|---|
| Children suspected with APD scores from dynamic EE evaluation | 0.89 | 0.09 |

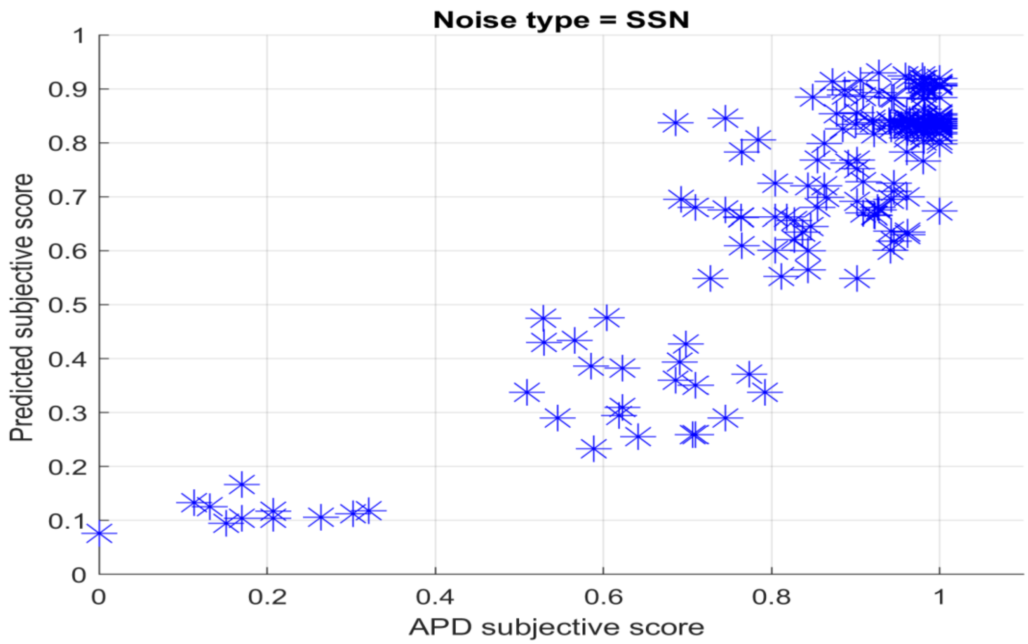



**Figure 5-4: Scatterplot showing the relationship between actual APD subjective scores and predicted scores.**

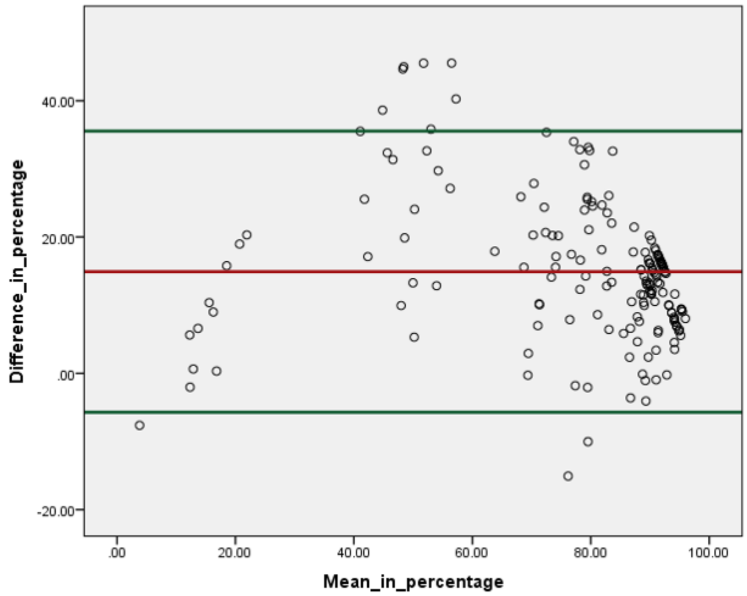



**Figure 5-5: Bland-Altman plot (APD subjective scores from DEE experiment versus predicted scores).**

### 5.1.3 Comparison between DEEDT and SEEDT models

It can be noted from the correlation analysis that both DEEDT and SEEDT models show approximately the same degree of correlation and standard error of estimation with APD subjective scores associated with the stationary background noise experiment. In addition, Bland-Altman plots demonstrated that both DEEDT and SEEDT models show approximately similar mean differences, which indicates the same bias in these predictors, for results associated with stationary background noise dataset. Hence, both DEEDT and SEEDT models could be considered as accurate models in predicting APD subjective scores associated with stationary background noise environment. On the other hand, the DEEDT model demonstrated a lower degree of correlation and higher standard error of estimation as well as greater amount of bias in predicting the subjective scores collected from non-stationary background noise, when compared with its performance in predicting subjective scores associated with the stationary background noise. Therefore, it is essential to derive generalized models to predict the corresponding subjective speech intelligibility scores of EE algorithms irrespective of the type of the background noise. Hence, in the following section, generalized versions of the speech intelligibility predictors are proposed by training models with APD subjective scores corresponding to both stationary and non-stationary background noise evaluations of dynamic and static EE.

## 5.2 Generalized models for predicting speech intelligibility

### 5.2.1 Weighted ModA (WModA) model

As discussed in Chapter 3 and 4, normalized ModA values showed lower correlation with subjective scores, which were collected from dynamic and static EE experiments. Hence, in order to find a better mapping between un-normalized ModA values and the subjective data, a data-driven approach is undertaken to derive an objective predictor in a manner similar to HASPI objective metric as explained in the next paragraph.

As discussed in Chapter 2, section 2.7.2, the area under the modulation spectrum in each frequency band is defined as $A_i$. It should be noted that in this thesis, we set the number acoustic frequency bands, *N*, to 8 (Equation 2.2), and the modulation rate is set to 32 Hz. Hence, the modulation areas in each of the eight-acoustic frequency channels are used as ModA features for training the model. Therefore, a weighted ModA metric was derived by computing eight modulation areas ($A_1$, $A_2$, $A_3$, $A_4$, $A_5$,$A_6$,$A_7$, and $A_8$) for each subjective score at each processing condition [viz. 496 scores (11 subjects with suspected APD x 16 dynamic EE processing conditions, (10 subjects with APD x 16 static EE processing conditions for SSN), and (10 subjects with APD x 16 static EE processing conditions for MTBN)]. Then, the optimal combination of the ModA features was decided through multivariate regression analysis, which was conducted by using the Regression Leaner feature in MATLAB. After training a model in Regression Learner application, a regression tree model achieved the lowest RMSE value, which was 0.1229. Furthermore, the regression tree model explained 88% of the variance in the subjective data.

### 5.2.2 Modified HASPI (MHASPI) model

A modified HASPI model is derived in a manner similar to DEEDT and SEEDT models. As we discussed in Chapter 3 and Chapter 4, the modified HASPI predictor is derived by computing HASPI features (i.e. c, $a_{Low}$, $a_{Mid}$, and $a_{High}$) for each subjective score at each processing condition [viz. 496 scores (11 subjects with suspected APD x 16 dynamic EE processing conditions, (10 subjects with APD x 16 static EE processing conditions for SSN), and (10 subjects with APD x 16 static EE processing conditions for MTBN)]. The optimal combination of HASPI features was then decided through multivariate regression analysis. The same regression model (i.e. the regression tree model, as Weighted Mod-A, achieves the RMSE value of 0.1232 and explains 88% of the variability of the subjective data.

### 5.2.3 Validating WModA and MHASPI models

Both WModA and MHASPI were trained with all APD subjective scores. Hence, new subjective data are needed to test with these models to verify the model performance in terms of the accuracy. Due to the fact that there was no new data available for testing, the most common approach in machine learning techniques was applied to test these models. Therefore, to validate WModA and MHASPI models, 80 % of the dataset was chosen randomly to be the actual training dataset, and the remaining 20 % to be the test dataset. As a result, these models iteratively trained and validated on these different sets [73]. Since, the APD dataset consists of 496 scores, 396 and 100 scores were split randomly to train and test datasets respectively. Regression tree model was again the best feature mapping model, for both weighted ModA and HASPI features. The RMSE value for WModA and MHASPI trained models were 0.1191 and 0.1313 respectively. In addition, the regression tree model based on weighted ModA and HASPI features explain 89 % and 86 % of the variance in the trained dataset. After that, the test dataset was used to validate the models. Figure 5 – 6 depicts the scatter plots of the predicted test scores versus the APD subjective test scores for MHASPI and WModA predictors. The scatter plots show that both predictors have values scattered around the diagonal. In addition, the validity of both MHASPI and WModA can be noted from Table 5.3, which shows the correlation coefficients and the standard errors of estimation. Furthermore, the Bland-Altman plots, which demonstrate the reliability of these models, based on MHASPI and WModA are displayed in Figures 5 – 7 and 5 – 8 respectively. It should be noted from these figures that the mean difference scores were 1.16 % and -2.45 % for MHASPI and WModA respectively, which approximately show a perfect agreement between the predicted and actual subjective data. Although WModA and MHASPI predictors showed approximately the same level of correlations as well as the same estimation error values and similar Bland-Altman plots, the WModA predictor is a reference-free objective predictor, unlike MHASPI. A reference-free objective predictor is highly attractive for online monitoring and optimization of speech intelligibility scores associated with the evaluation of future EE algorithms when compared to full-reference MHASPI objective predictor. As the subjective evaluation of novel EE algorithms is a time-consuming and expensive task, WModA could be a better objective predictor candidate compared to MHASPI to estimate the APD subjective scores associated with evaluating of novel EE algorithms. Therefore, in the next section (i.e. 5.3), the performance of a companding algorithm in the presence of both stationary and non-stationary background noise is evaluated by applying the proposed reference-free objective predictor (i.e. WModA) to estimate the speech intelligibility associated with the companding algorithm.

**Table 5-3: Correlation coefficient and standard error of estimation for WModA and MHASPI.**

| Model_under_test | ρ | σ |
|---|---|---|
| MHASPI | 0.94 | 0.11 |
| WModA | 0.95 | 0.12 |

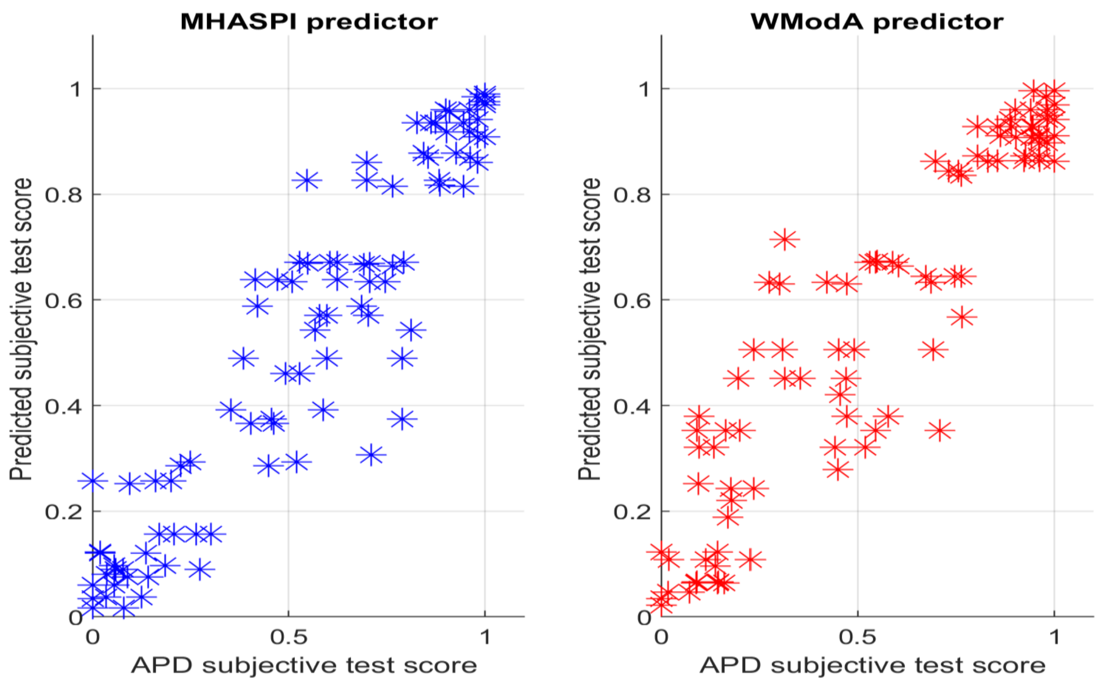



**Figure 5-6: Scatter plot of predicted and subjective test scores for MHASPI and WModA predictors.**

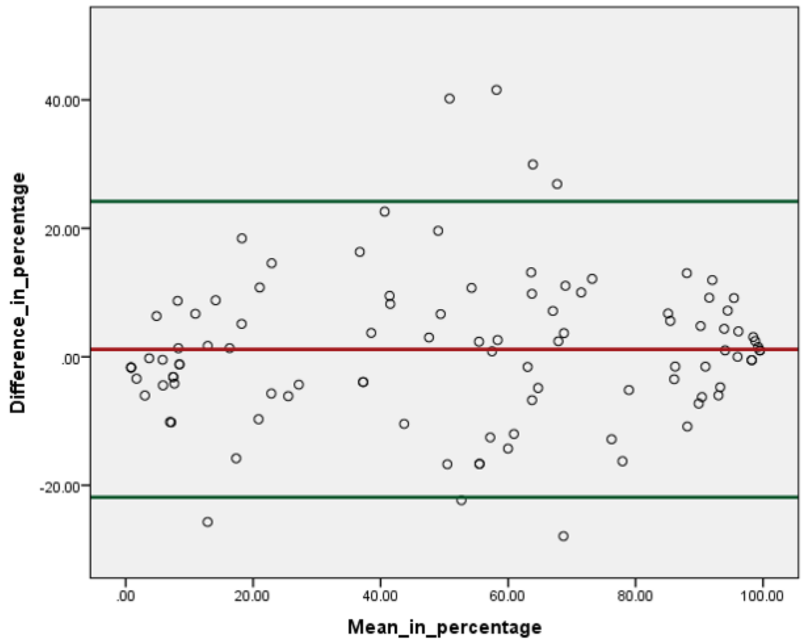



**Figure 5-7: Bland-Altman plot (APD subjective test scores versus predicted scores from MHASPI predictor).**

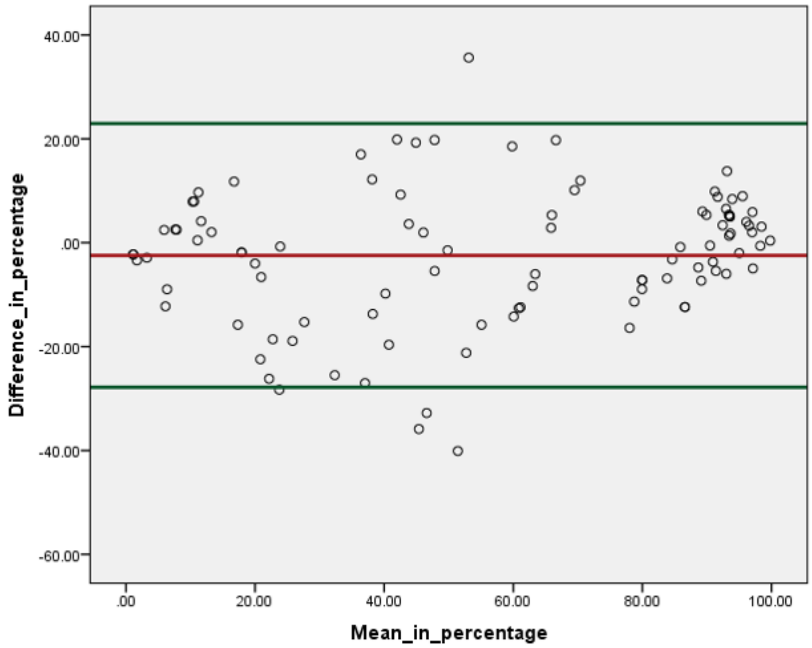



**Figure 5-8: Bland-Altman plot (APD subjective test scores versus predicted scores from WModA predictor).**

## 5.3 Companding Architecture

The companding strategy described in [32] and [33] was used to evaluate the effectiveness of spectral enhancement for improving speech recognition in people with ANSD and children with APD. Although the companding architecture was developed on an iPad platform, the companding algorithm development, debugging, and testing was completed using MATLAB 2016a on a personal computer platform. It is pertinent to point out that, in this chapter, offline evaluation of the companding is considered, and realtime implementation of the companding algorithm is out of scope for the present study. As it is described in Chapter 2, the benefit of the companding architecture in CI users and individuals with ANSD has been achieved for both phoneme and sentence recognition test in quiet and steady-state speech-shaped noise. However, the previous research considered the subjective evaluation of companding algorithm in the presence of only stationary background noise. Although the present work builds on the earlier published results, the objective evaluation of companding algorithm in the presence of both stationary and non-stationary background noise is a novel contribution. Therefore, one of the main goals of this study is to evaluate the performance of the commanding architecture in the presence of different types and levels of background noise objectively using the non-intrusive metric (i.e. WModA). Furthermore, since the previous research indicated that the performance of the companding algorithm reduces in the presence of background noise [34], the effectiveness of incorporating the MHA NR algorithm as a front-end to the companding algorithm is also investigated.

### 5.3.1 MATLAB implementation

Figure 5 – 9 illustrates the block diagram for a single channel companding architecture. As it can be seen from Figure 5 – 9, the algorithm consists of two individual blocks: compression and expansion. The input speech signal was first divided into 50 frequency channels using a bank of relatively broad band bandpass filters (BBBPFs). Next, the signal in each channel was subjected to amplitude compression. The compression index ($n_1$), which was set to 0.3, and the output of the envelope detector (ED) determined the amount of compression. The compressed speech signal was then passed through a relatively narrow bandpass filters (NBBPFs) before being expanded in the expansion block. The amount of expansion was determined by the corresponding ED output and the ratio $(n_2\text{-}n_1)/n_1$, where $n_2$ is the expansion index, which was set to 1. Subsequently, the outputs from all the channels were combined to obtain the processed signal. It is pertinent to point out that the RMS value of the companded signal was equated to that of the original input signal. It also should be noted that both of these filters (e.g. BBBPFS and NBBPFS) had the same resonant frequency in the same channel and are described by the following transfer functions:

$$F_i'(s) = \left( \frac{2\left(\frac{\tau_i}{q_1}\right)s}{\tau_i^2 s^2 + 2\left(\frac{\tau_i}{q_1}\right)s + 1} \right)^2 \qquad (5.1)$$

$$G_i'(s) = \left( \frac{2\left(\frac{\tau_i}{q_2}\right)s}{\tau_i^2 s^2 + 2\left(\frac{\tau_i}{q_2}\right)s + 1} \right)^2 \qquad (5.2)$$

where the subscript *(i)* refers to the channel index, $\mathrm{BBBPFS_i(s)} = \mathrm{F_i'^2(s)}$ and $\mathrm{NBBPFS_i(s)} = \mathrm{G_i'^2(s)}$, and $q_1$ and $q_2$ are filter parameters set to 2 and 12, respectively [33]. To create $\mathrm{BBBPFS_i(s)}$ and $\mathrm{NBBPFS_i(s)}$, $F_i'(s)$ and $G_i'(s)$ were each cascaded with themselves. The bilinear transform was used to derive the digital versions of the aforementioned filters. Furthermore, in order to reduce the interference across channels, zero-phase filtering was used. The resonant frequencies for each channel were logarithmically spaced between 100 and 8000 Hz. The resonant frequency, $f_{r,i}$, is related to $\tau_i$ by the following function:

$$f_{r,i} = \frac{1}{2\pi\tau_i} \qquad (5.3)$$

Envelope detection was performed using full-wave rectification followed by a first order lowpass Butterworth filter. The resonant frequency of the lowpass filter was calculated with the following function:

$$f_{ED,i} = \frac{f_{r,i}}{\omega} \qquad (5.4)$$

where $\omega$ was chosen to be 40 [33].

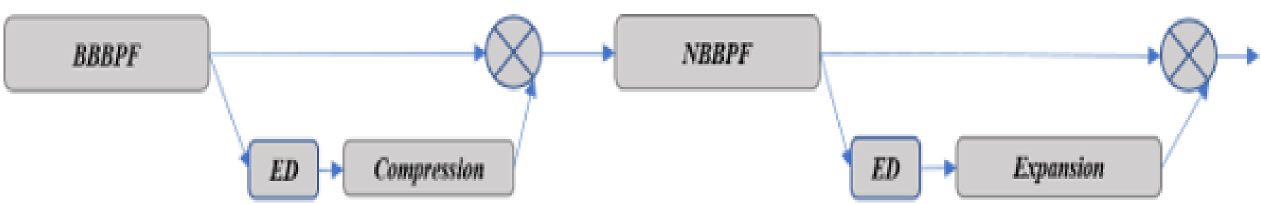



**Figure 5-9: A single channel within the companding architecture** [33]**.**

## 5.4 Two-tone suppression fundamentals

The NBBPF differentiates the companding architecture from traditional compression strategies and allows for two-tone suppression. A high-level description, using Figure 5-10, of how this strategy results in two-tone suppression is provided in the next paragraph [32].

Assume BBBPF is broad and almost perfectly flat, while NBBPF is sharply tuned. A sinusoid, $A_1$, is at the resonant frequency of the channel and a sinusoid of larger amplitude, $A_2$, is at a different frequency. After filtering by FBBPF, $A_1$ and $A_2$ are plotted in Figure 5-10. The gain of the compression block is determined by the envelope detector, which is most heavily influenced by the stronger sinusoid, $A_2$. $A_2$ is transformed to $B_2$ and $A_1$ is transformed to $C_1$. NBBPF heavily suppresses $A_2$ since it is off the resonant frequency, meaning $C_1$ will be the only sinusoid passing through NBBPF. $C_1$ is then expanded to get $D_1$. Therefore, $A_1$ has been suppressed to $D_1$ by an off-frequency strong tone, $A_2$. $B_1$ illustrates how the amplitude of $A_1$ would be unaffected by companding if $A_2$ had not been present. The stronger tone has the effect of suppressing the weaker tone, showing the spectral enhancement produced by companding. It should be noted here that an analytical proof of the spectral enhancement achieved by the companding architecture is given in [32].

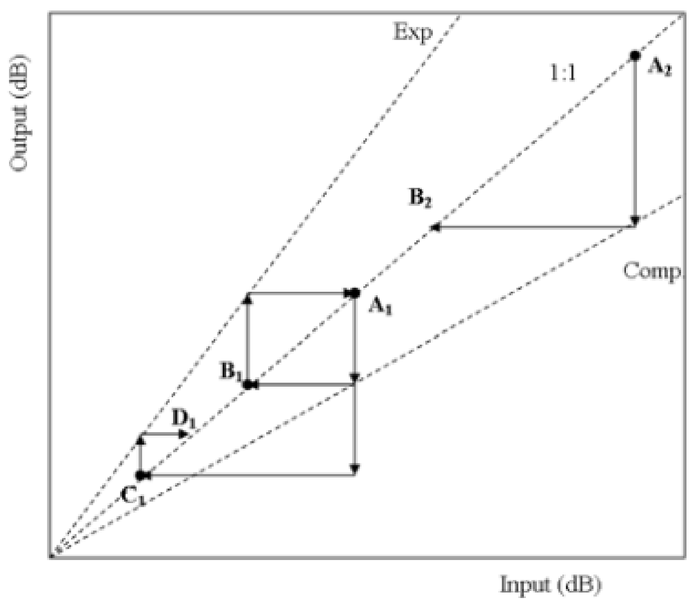



**Figure 5-10: Graphical illustration of companding algorithm** [32]**.**

## 5.5 iPad development

The companding architecture was developed on an iPad platform as an iOS application for offline processing as mentioned in Chapter 2. The application was developed by converting the MATLAB script of companding algorithm line-by-line into Swift programming by using Xcode as the IDE and the VDSP portion of the Accelerate Framework. It is also pertinent to point out that the iPad platform development of companding architecture was motivated since our centre at Western University (National Centre for Audiology) has developed a software program to conduct frequency resolution test on the iPad platform. Therefore, integrating the companding architecture within the frequency resolution test software on the iPad platform allows a clinician to vary the companding algorithm parameters (e.g. number of frequency channels, $n_1$, and $n_2$) to compensate the patient's frequency contrast deficit. Figure 5 – 11 is an example stimulus that shows the companding output based on iOS development is identical to the companding output, which is generated from MATLAB. In order to verify that the developed companding algorithm based on iOS generates the same output as the MATLAB development, the output speech file from iOS is first converted to binary file. Then, the binary file from iOS is loaded in MATLAB.

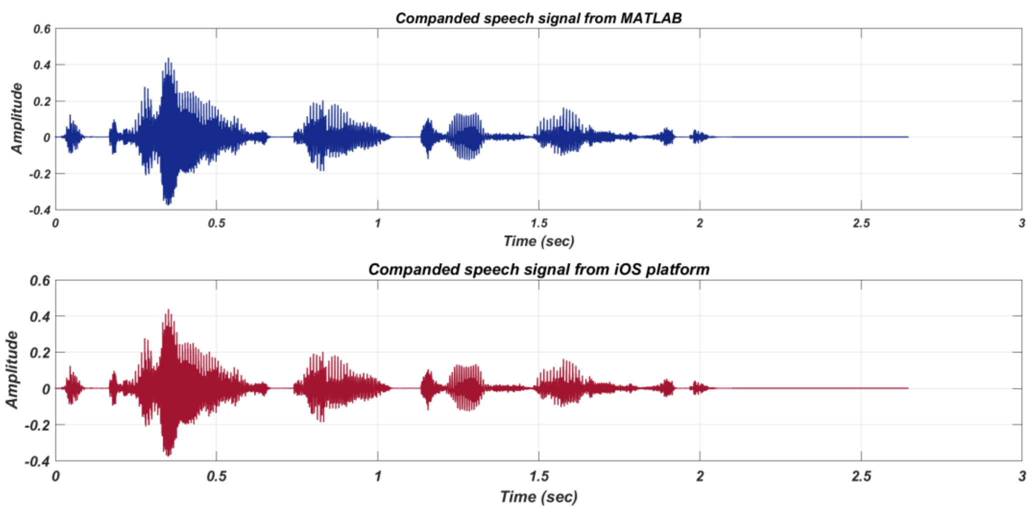



**Figure 5-11: Comparison of the companded speech stimulus between MATLAB and iPad platforms.**

## 5.6 Experimental methodology and results

### 5.6.1 Clean speech database and method

The HINT clean speech sentences were used in evaluating the companding algorithm. The clean speech sentences were corrupted by two different types of noise, SSN and MTBN. The noisy speech stimuli were then processed by the companding algorithm. In addition, in order to assess the benefits of incorporating a NR algorithm as a front-end to the companding algorithm, the MHA NR algorithm was applied to the noisy speech prior to the application of the companding architecture. Hence, the database contained 25 lists x 10 sentences/list x 2 types of background noise (SSN and MTBN)x 3 companding settings (companded, MHA NR & companded, and unprocessed) x 4 SNRs (3dB, 0 dB, -3 dB, and -6 dB) = 6000 stimuli.

### 5.6.2 Long-term average power spectrum

Figure 5 – 12 displays a sample experimental result wherein the long-term averaged spectra of a stationary noisy speech (SNR = 0 dB) are compared across three processing conditions: unprocessed, companding alone, and a combination of MHA NR and companding. It can be seen that companding alone does sharpen the speech spectral peaks. However, applying both MHA NR and companding to noisy speech at the same SNR (SNR = 0 dB) results in a significantly better sharpening of the spectral peaks.

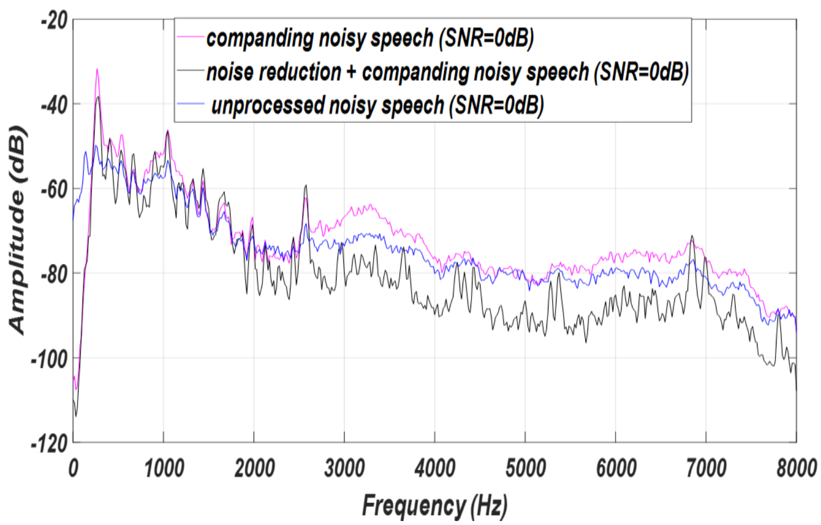



**Figure 5-12: Comparison of long-term average power spectra.**

## 5.7 Objective assessment

Objective assessment of companding algorithm was carried out in a manner similar to the following: a list of 10 sentences were randomly chosen from both SSN and MTBN database for each processing condition, and WModA objective speech intelligibility predictor was applied to all 10 sentences in the list. The average scores across these 10 sentences were used for benchmarking the companding algorithm in the presence of both stationary and non-stationary background noise. Figures 5 – 13 and 5 – 14 display the results for stationary and non-stationary background noise for a range of SSN values between -6 to 3 dB respectively, where the 'Companding', 'MHACompanding', and 'UP' conditions represent (1) the companding, (2) the combination of MHA NR and companding, and (3) the unprocessed. Results from these figures reveal that the application of MHA NR algorithm can improve the performance of companding architecture significantly compared to unprocessed condition, irrespective of the type of the background noise and SNR value. However, the amount of improvement is much higher for stationary background noise.

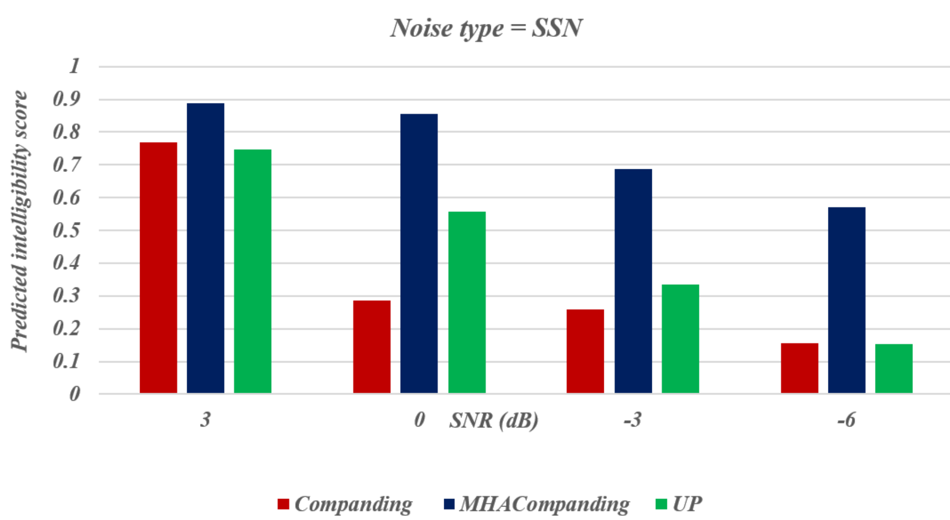



**Figure 5-13: Objective assessment of companding algorithm in the presence of stationary background noise.**

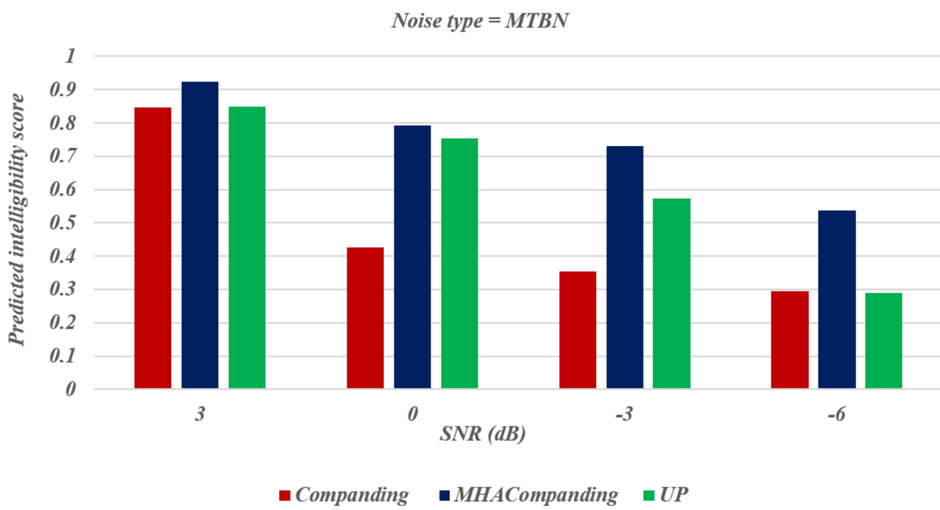



**Figure 5-14: Objective assessment of companding algorithm in the presence of non-stationary background noise.**

Objective analysis in the present study demonstrates that the sole application of companding architecture is not beneficial in improving the speech intelligibility when the SNR is poor regardless of the background noise type. It is pertinent to point out that overall, the predicted results associated with this study are in a very good agreement with previous research by Narne et al. [34] , which was indicated that companding processing by itself was inferior in consonant recognition experiment for ANSD subjects at lower SNRs ( e.g. SNR = 0) compared to higher SNRs (e.g. SNR = 15 dB). Although, subjective measurements are costly and time-consuming processes, subjective evaluation of companding algorithm across different types and levels of background noise is recommended as future work for validating the objective scores computed from a proposed non-intrusive objective predictor (i.e. WModA).

## 5.8 Summary

In this chapter, the robustness of individual DEEDT and SEEDT models were evaluated by testing with APD subjective scores, which were collected from static EE and dynamic EE experiments respectively. Due to the fact that both of these models are more accurate and reliable in predicting subject scores associated with stationary background noise environment compared with predicting the non-stationary dataset, a generalized version of intrusive and non-intrusive objective models (e.g. MHASPI and WModA) were derived to predict the perceptual impact of novel EE algorithms regardless of the background noise environment. Since, the WModA model is a reference-free objective predictor, unlike the MHASPI model, it was applied to predict the speech intelligibility scores extracted from the evaluation of the companding algorithm across different types and levels of background noise.

Experiments were conducted to explore the performance of the companding algorithm in the presence of different types and levels of background noise as well as evaluating the effectiveness of companding architecture by incorporating the MHA NR algorithm. Predicted results showed that the incorporation of MHA NR algorithm does expand the effectiveness of the companding algorithm over a wider SNR range. These results can potentially guide the choice and activation of companding architecture as one of the signal processing strategies for hearing aid applications to improve speech perception in individuals with ANSD and children with APD. In the next chapter, the effectiveness of binaural dichotic processing technique is evaluated subjectively with adults with HI and normal hearing, at different types and levels of background noise.

# Chapter 6

## 6 Binaural dichotic signal processing

As discussed in Chapter 2, individuals with SNHL experience a significant challenge in speech perception in the presence of background noise since SNHL patients possess poor frequency resolution. In addition, the effectiveness of the dichotic processing technique for speech perception for individuals with SNHL was discussed in Chapter 2. In this chapter, the development and assessment of the dichotic processing algorithm for a typical binaural hearing aid application is investigated across different processing conditions. It is pertinent to point out that the dichotic processing scheme development, debugging, and testing was completed using MTLAB 2017 on a personal computer platform. It is also pertinent to point out that, in this chapter, offline evaluation of the dichotic processing is considered, and realtime implementation of the dichotic processing is out of scope for the present study.

As described in Chapter 2 in section 2.4, previous studies only explored the assessment of dichotic processing after application to short segments of speech (consonants, vowels, and words) [42] , [45], [43], [44], and [38]. Furthermore, a comprehensive assessment of the impact of background noise on the performance of dichotic processing is lacking as explained in the following: either the studies evaluated the effectiveness of dichotic processing with HI subjects only in quiet environments, or they simulated different degrees of hearing loss in NH participants by adding Gaussian white noise or pink noise after dichotic processing. In addition, the impact of different noise types (stationary vs. non-stationary) has not been previously investigated. Therefore, the objective of the present study is to evaluate the effectiveness of the dichotic processing scheme on sentence-level speech perception by adults who have NH and HI (i.e. SNHL) across different types and levels of background noise. In general, this chapter contributes novel results on the performance of the dichotic processing by investigating the following research questions: (1) does the dichotic processing algorithm enhance speech intelligibility for adults with SNHL? (2) how does the dichotic processing scheme perform in a variety of noisy conditions? (3) how does the MHA NR algorithm, which is incorporated as a front-end to the application of dichotic processing scheme, affect the performance of dichotic processing algorithm across different types and levels of background noise?

### 6.1 Experiment I

The effectiveness of dichotic processing scheme is examined with NH and HI participants in the presence of stationary background noise (i.e. SSN).

### 6.1.1 Method

#### 6.1.1.1 Participants

A total of 20 individuals including 10 individuals with SNHL and 10 individuals with NH participated in this study. All the participants were native speakers of English. Group I included 10 individuals with NH, five males and five females ranging in age from 18 – 30 years. The individuals with NH had normal pure-tone threshold at octave frequencies from 250 Hz to 8000 Hz and had no history of any listening difficulties. These individuals were audiology students, who were volunteers from Western University.

**Table 6-1: Audiological profile of individuals with SNHL.**

| Subject no | Age (yr)/Sex | Pure-tone average of left ear (dB HL) | Pure-tone average of right ear (dB HL) | Degree of hearing loss |
|---|---|---|---|---|
| 1 | 37/F | 34.38 | 25.63 | Mild |
| 2 | 79/M | 45.71 | 47.14 | Moderate |
| 3 | 76/M | 66.25 | 51.25 | Moderate-severe |
| 4 | 79/M | 37.5 | 35.63 | Mild |
| 5 | 81/F | 40 | 37.5 | Mild |
| 6 | 78/M | 46.25 | 40.63 | Moderate |
| 7 | 60/F | 38.13 | 37.5 | Mild |
| 8 | 81/M | 65.63 | 55.63 | Moderate-severe |
| 9 | 72/F | 43.75 | 46.88 | Moderate |
| 10 | 82/M | 56.88 | 51.25 | Moderate-severe |

Group II included 10 individuals, four women and six men, who had been previously diagnosed with SNHL. Table 6 -1 shows the audiologic profile of the participants. The age of the participants ranged from 37 – 82 years. The mean pure-tone average (average thresholds for frequencies from 250 Hz to 8000 Hz) was 42.90 dB HL for the right ear and 47.45 dB HL for the left ear. Four participants had a mild hearing loss, 3 participants had a moderate hearing loss, and 3 participants had a moderate-to-severe hearing loss. The participants with SNHL were recruited from clients registered at the Audiology Clinic at the University of Western Ontario, Ontario, Canada. It should be noted that all the participants were native speakers of English. It is also pertinent to point out that the hearing-impaired participants had symmetric and bilateral SNHL without having any other disorders (e.g. cognitive).

#### 6.1.1.2 Stimuli

The noisy speech database was created for collecting the speech intelligibility data from the participants in a manner described in Chapter 3 and 4 (i.e. the clean speech sentences were taken from the HINT database). The clean speech sentences were mixed with stationary background noise (viz. HINT SSN) at different SNRs. The noisy speech stimuli were then processed by the dichotic processing algorithm, described in more detail in the next section. Furthermore, in order to assess the benefits of the sole application of a NR algorithm and its combination as a front-end to dichotic processing scheme, the MHA NR algorithm was applied to the noisy speech prior to the application of dichotic processing .This led to a total of 25 lists x 10 sentences/list x 4 processing condition settings (sole application of dichotic, sole application of MHA NR, combination of MHA NR and dichotic, and unprocessed) x 4 SNRs (3 dB, 0 dB, -3 dB, and -6 dB) = 4000 stimuli in the Experiment 1 database.

#### 6.1.1.3 Dichotic processing scheme

Figure 6 – 1 illustrates the building blocks for implementing dichotic processing scheme in this research study. It can be seen from this figure that the input speech was first split into 30 frequency bands by 4$^{th}$ order Gammatone filters. Then, the 15 odd filters (1$^{st}$, 3$^{rd}$, 5$^{th}$, …, 29$^{th}$) and 15 even filters (2$^{nd}$, 4$^{th}$, 6$^{th}$, …, 30$^{th}$) bands were processed by a separate synthesis filterbanks to generate Output_Left and Output_Right signals, respectively. The analysis and synthesis building blocks are briefly described in the following paragraphs.

Previous research study by Kulkarni et al. [38] concluded that the dichotic processing scheme, whose implementation was based on auditory critical bandwidth comb filters, achieved a greater improvement in speech perception compared to the fixed band width filterbank design. Hence, in this research study, the auditory filterbank was constructed from a more efficient implementation technique which is explained in the next paragraph.

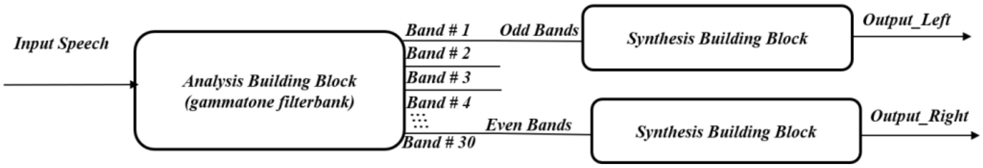



**Figure 6-1: Block diagram of the dichotic processing scheme.**

### 6.1.2 Gammatone filter design

The digital version of a gammatone filter was achieved by applying the impulse invariance technique. In other words, the digital filter was derived from the sampled version of the analog Gammatone impulse response, which is shown in Equation 6.1 [74], by iteratively applying the Z transform.

$$g_{\gamma}(n) = n^{\gamma-1}.\tilde{a}^{n}, n \geq 0 \qquad (6.1)$$

$$with\ \ \tilde{a} = \lambda.exp(i\beta)$$

where $\lambda$ is the bandwidth parameter, $\beta$ is the oscillation frequency, $\gamma$ is the filter order, and $n$ is the sample index.

#### 6.1.2.1 Filterbank design

An auditory filterbank was constructed from combining the 4th order Gammatone filters based on an impulse-invariant, all-pole design. The bandwidth of the auditory filterbank was computed as a function of its center frequency by considering the equivalent rectangular bandwidth (ERB) of the auditory filters in the cochlea [74]. The corresponding ERB value as a function of frequency in Hz is computed by Equation 6.2.

$$ERB(f) = q.log\left(1 + \frac{f}{L.q}\right) \qquad (6.2)$$

$$f = \left(exp\left(\frac{ERB}{q}\right) - 1\right).L.q,\ \text{where } L = 24.7, q = 9.265$$

In order to design a bank of Gammatone filters that are equally spaced on the ERB scale, the following steps were followed; starting with a base frequency of 1000, which indicates that one of the filters in the filterbank has a center frequency of 1000 Hz, calculating the corresponding value on the ERB scale using Equation 6.2 and derives the center frequencies of the other filters by taking fixed steps on the ERB scale towards higher and lower frequencies [74]. It is pertinent to point out that the step size on the ERB scale determines the density of the filters. It is also pertinent to point out that in this research study, the Gammatone filter bank design consists of 30 auditory filters between lower and higher center frequencies of 70 and 6700 Hz respectively that operates at a sample frequency ($f_s$) of 16000 Hz. In addition, it should be noted that, the centre frequency of 1000 Hz was used as the base frequency and the density of the filters in the filterbank was chosen to be one ERB. Figure 6 – 2 shows the magnitude frequency response of the filterbank design that was utilized for binaural dichotic processing in this research study. The selected scheme generated the 30 Gammatone filters that covered the 1 - 8000 Hz region (the centre frequencies of each frequency band ($f_c$) and their corresponding ERBs are shown in Table 6 – 2.

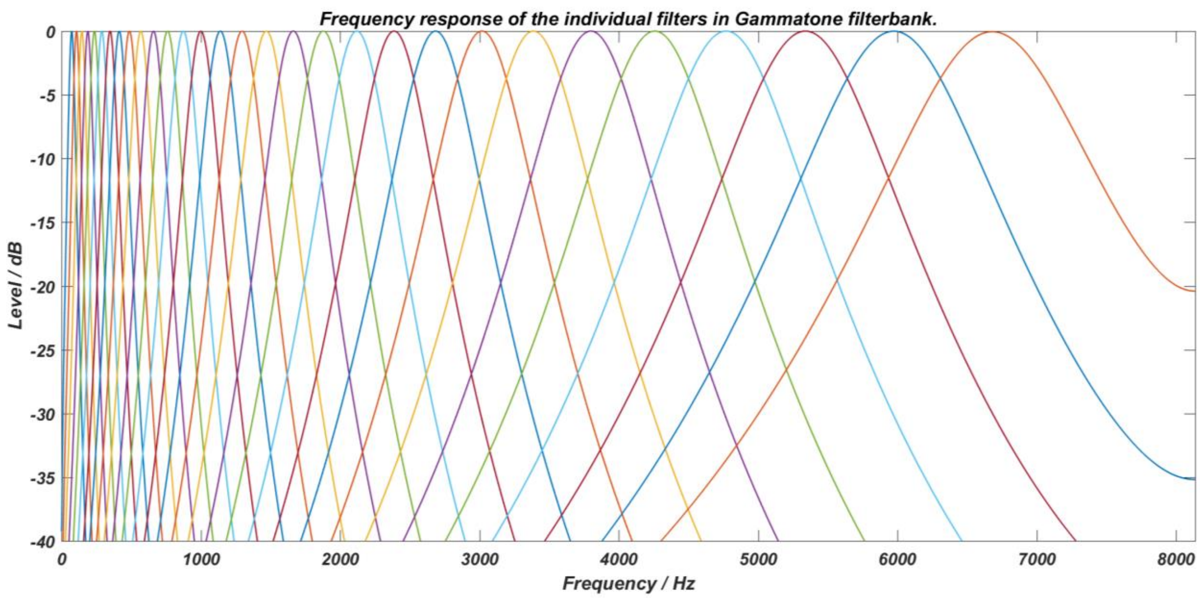



**Figure 6-2: Frequency response of the individual filters in the Gammatone filterbank.**

**Table 6-2: Bands in the Gammatone filterbank; Fc: center frequency, ERB, Equivalent Rectangular Bandwidth.**

| Band # | Fc (Hz) | ERB | Band # | Fc (Hz) | ERB |
|---|---|---|---|---|---|
| 1 | 73.24 | 32.60 | 16 | 1296.07 | 164.59 |
| 2 | 107.67 | 36.33 | 17 | 1469.87 | 183.35 |
| 3 | 146.02 | 40.46 | 18 | 1663.48 | 204.25 |
| 4 | 188.74 | 45.07 | 19 | 1879.16 | 227.52 |
| 5 | 236.34 | 50.21 | 20 | 2119.41 | 253.46 |
| 6 | 289.36 | 55.93 | 21 | 2387.05 | 282.34 |
| 7 | 348.42 | 62.31 | 22 | 2685.19 | 314.52 |
| 8 | 414.21 | 69.41 | 23 | 3017.31 | 350.37 |
| 9 | 487.50 | 77.32 | 24 | 3387.29 | 390.30 |
| 10 | 569.15 | 86.13 | 25 | 3799.43 | 434.78 |
| 11 | 660.10 | 95.95 | 26 | 4258.55 | 484.34 |
| 12 | 761.41 | 106.88 | 27 | 4769.99 | 539.54 |
| 13 | 874.27 | 119.06 | 28 | 5339.72 | 601.03 |
| 14 | 1000 | 132.63 | 29 | 5974.39 | 669.53 |
| 15 | 1140.06 | 147.75 | 30 | 6681.39 | 745.84 |

### 6.1.2.2 Frequency synthesis block design

It is pertinent to point out that a reconstruction of the input signal can not be conducted by directly summing up the filterbank output channels since the impulse responses of the different frequency channels have different fine structure and group delay. Hence, a low-delay (e.g. 4 ms) resynthesis of the filterbank output is proposed based on a sampled all pass filter design combined with a delay line [74]. The fine structure and the envelope of the impulse response for each frequency channel is delayed by 4 ms. Therefore, all frequency bands have their envelope maxima and their fine structure maxima at the same instant of time. The synthesis algorithm is introduced in a manner described in the following: the complex output signals from the filterbank, $\widetilde{y_k}$ *(n)* are multiplied with the frequency band-dependent complex phase factors, $\widetilde{\mathrm{b_k}}$ , where k and n are the band and sample indices respectively, which is shown in Equation 6.3.

$$\widetilde{y'_k}(n) = \widetilde{b_k}.\widetilde{y_k}(n), 0 \leq k < K \tag{6.3}$$

where $\widetilde{\mathrm{b_k}}$ is a phase factor with magnitude 1, which is calculated from Equation 6.4 for a maximum of the fine structure at the band-dependent time ($t_k$), where $f_k$ is the centre frequency of the band k in Hz. It should be noted that $t_k$ denotes the time that the envelope of the respective impulse response is maximum or the desired group delay for such cases that the maximum envelope is leader in time compared to the desired group delay or the maximum envelope is lagger in time than the desired group delay respectively.

$$\widetilde{b_k} = exp(i.\emptyset_k)\,,\emptyset_k = -2\pi.f_k.t_k \tag{6.4}$$

Due to the fact that only the real part is used for the synthesis, Equation 6.3 is evaluated for the real part, which is shown in Equation 6.5.

$$y'_k(n) = cos(\phi_k)\,.Re\big(\widetilde{y_k}(n)\big) - sin(\emptyset_k)\,.Im(\widetilde{y_k}(n)) \tag{6.5}$$

After that, the real part $y'_k(n)$ are delayed by a band-dependent amount of $\Delta n_k$ samples as shown in Equation 6.6, where int() refers to the nearest integer operation. In addition, $\Delta t_k$ denoted the difference in time between the desired group delay (e.g. 4ms) and the point in time that the envelope of the respective impulse response is maximum. It is pertinent to point out that $\Delta t_k$ should be set to zero in such the case that the desired group delay is former in time compared to the maximum envelope of the respective impulse response.

$$\Delta n_k = int(\Delta t_k.f_s) \tag{6.6}$$

Therefore, the delayed version of the real parts, $y'_k(n)$, are shown in Equation 6.7.

$$y''_k(n) = y'_k(n - \Delta n_k) \tag{6.7}$$

The synthesized output signal is finally computed by a weighted sum across all frequency bands (K = 30) as shown in Equation 6.8, where $g_k$ denotes the band-dependent gains.

$$y'''(n) = \sum_{k=0}^{K-1} g_k . y''_k(n) \tag{6.8}$$

Hohmann [74] concluded that the reconstructed speech signal with the analysis-synthesis filterbank with a total delay of 4 ms achieved a nearly perfect reconstruction input speech (i.e. the perceptual difference between the input and reconstructed output speech signal is barely audible). Hence, in this research study, the same delay time value (i.e. 4 ms) was used for the analysis-synthesis system.

### 6.1.3 Audio presentation and speech intelligibility measurement

Speech perception in noise was measured in a manner similar to Chapter 3 and 4 (viz. using the custom software developed in our laboratory, as shown in Figure 3 – 7). The stimuli were presented binaurally through the Sennheiser HDA 200 headphones. The presentation level was set to 65 dB Sound Pressure Level (SPL) for NH subjects. For HI listeners, a separate procedure was followed as detailed below.

For each HI participant, the input diotic and dichotic stimuli at 65 dB SPL were filtered such that necessary frequency-specific amplification is provided based on their hearing loss profile. The target frequency-gain response for the left and right ears was derived using the real ear insertion gains (REIGs) prescribed by the Desired Sensation Level (DSL) 5.0 algorithm [75]. A 100-tap Finite Impulse Response (FIR) filter was designed to match the respective target frequency responses and applied to the test stimuli. The filtered digital stimuli were converted to their analog versions through the sound card and subsequently passed through a programmable attenuator and a headphone amplifier. The combination of the programmable attenuator and amplifier ensured that the presentation levels did not exceed the loudness comfort levels. Thus, the presentation level of the stimuli was individualized based on the hearing loss of the participant. Throughout and end at the end of the experiment, the HI participants provided the feedback on the perceived loudness of test stimuli, and with all HI participants, the stimuli were perceived at a comfortable level and of equal loudness. The subjective testing with HI listeners was conducted in a double-walled sound booth room.

## 6.2 Results

The averaged speech intelligibility scores along with their standard deviation for the two different participant groups (i.e. NH and HI) are illustrated in Figures 6 – 3 and 6 – 4, where the “up”, “Dichotic”, “MHA”, and “MHADichotic” conditions represent the unprocessed, dichotic processing, MHA NR, and a combination of MHA NR and dichotic processing of noisy stimuli respectively at different SNR values. It can be noted from Figure 6 – 3 that the speech intelligibility scores for dichotic processing stimuli were better for unprocessed speech regardless of the SNR condition. However, the improvement observed was significantly less for SNR = 3, 0, and -3 dB compared to SNR = -6 dB.

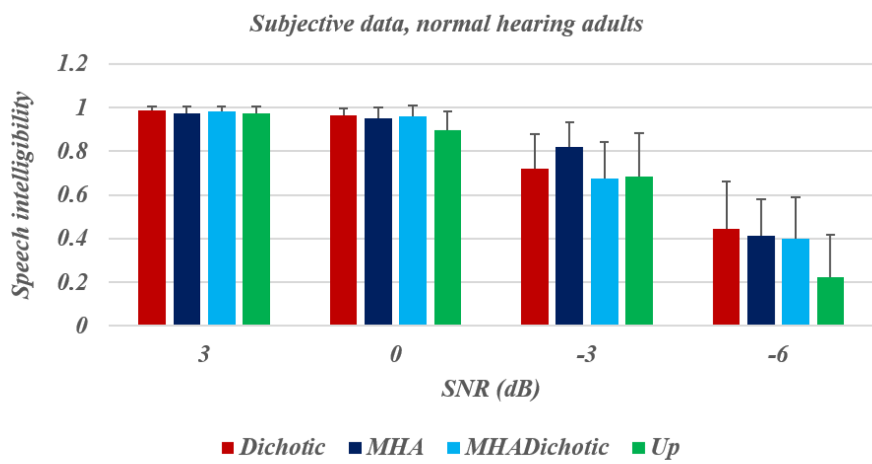



**Figure 6-3: Averaged speech intelligibility scores for adults with NH.**

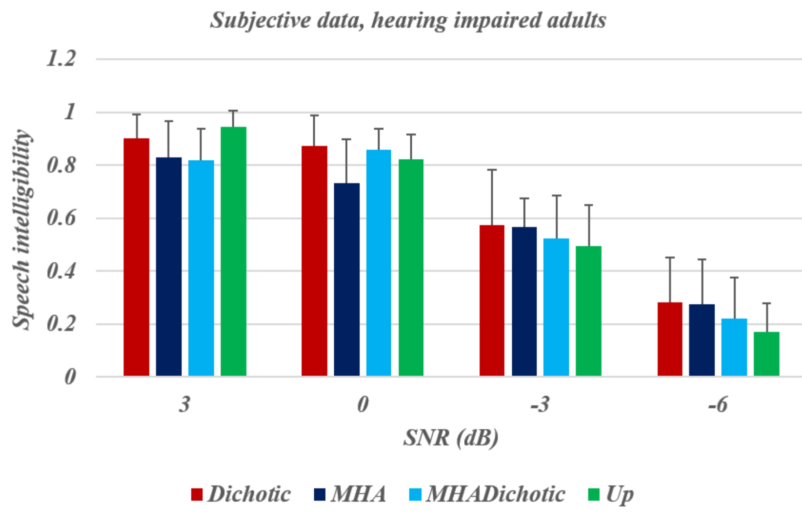



**Figure 6-4: Averaged speech intelligibility scores for adults with HI.**

It can be seen from Figure 6 – 4 that the speech intelligibility scores for dichotic processing condition were higher than those for unprocessed condition for SNR = 0, -3, and -6 dB. However, the improvement observed was significantly higher for SNR = -6 dB condition when compared with SNR = 0 and -3 dB conditions. In addition, the unprocessed scores associated with HI were less than the ones observed for NH participants irrespective of the SNR value. Furthermore, the incorporation of MHA NR as a front-end to dichotic processing is not beneficial in improving the speech intelligibility regardless of the SNR condition and participant group.

### 6.2.1 Statistical analysis

To evaluate the effect of processing (unprocessed, dichotic, MHA NR, and a combination of MHA NR and dichotic) in different SNR conditions, repeated measures ANOVA was conducted with processing and SNR as the within-subject factors for the results obtained from the NH and HI participants in a manner similar to Chapter 3 and 4. It should be noted that Mauchly's test of sphericity was violated for the SNR variable ($\chi^2(5) = 20.035$, $p = 0.001$), so the Greenhouse-Geisser correction was used for this condition ($\varepsilon = 0.643$). There was a significant main effect of processing ($F(3, 54) = 9.12$, $p < 0.001$) and SNR ($F(1.93, 34.70) = 348.18$, $p < 0.001$) parameters. In addition, there was a significant interaction between the processing and SNR variables ($F(9, 162) = 6.64$, $p < 0.001$), suggesting that the relative performance of different combinations of dichotic processing scheme depended on the SNR value. Furthermore, there was a statistically significant interaction between the processing and the subjective group (NH vs. HI), which is indicating that changing the processing condition did not have a similar effect across both groups.

To further analyze this interaction, Bonferroni pairwise comparison was conducted for the NH and HI subjective data at different processing and SNR values. Salient outcomes of this analysis for HI participant group include: (1) The scores associated with dichotic processing were significantly better than unprocessed scores only at SNR = -6 dB, while unprocessed condition was significant compared to dichotic condition only for SNR = 3 dB. Furthermore, the performance of dichotic and unprocessed conditions was statistically similar at SNR = 0 and SNR = -3 dB. (2) The scores associated with MHA NR were significantly worse compared to scores achieved by dichotic processing at SNR = 3 and 0 dB, while the performance of MHA NR and dichotic processing was statistically similar at SNR = -3 and -6 dB. (3) The scores associated with a sole application of MHA NR or its application as a front-end to dichotic processing were significantly lower compared to scores resulted from unprocessed at SNR = 3 dB, while at the other SNR values, their performance was statistically similar. It should be noted that SPSS outputs from subjective experiment of the dichotic processing scheme can be found in Appendix D of this thesis.

Major outcomes of the NH analysis include : (1) the performance of dichotic processing is statistically better compared to unprocessed condition only at SNR = -6 dB, (2) the scores associated with MHA NR were statistically similar to dichotic processing regardless of the SNR values, and (3) the incorporating of the MHA NR as a front-end to dichotic does perform statistically similar compared to the dichotic processing performance irrespective to the SNR values.

## 6.3 Experiment II

Usefulness of the dichotic processing technique in enhancing speech intelligibility in individuals with NH and SNHL in the presence of non-stationary (MTBN) background noise was evaluated in this experiment.

### 6.3.1 Participants

A total of 20 subjects including 10 NH and 10 HI individuals, who were distinct from Experiment I participants, participated in the non-stationary background noise evaluation of dichotic processing. Group I consisted of 10 NH subjects, five males and five females ranging in age from 18 – 30 years. Similar to Experiment I, the NH participants had normal pure-tone thresholds at octave frequencies from 250 Hz to 8000 Hz and had no history of any listening difficulties. These individuals were again Audiology students, who were volunteers from Western University.

Group II included 10 individuals, four women and six men, who had been previously diagnosed with SNHL. Table 6.3 shows the audiologic profile of the participants. The age of the participants ranged between 27 – 81 years. The mean pure-tone average (average thresholds for frequencies from 250 Hz to 8000 Hz) was 46.87 dB HL for the right ear and 48.08 dB HL for the left ear. Four participants had a mild hearing loss, two participants had a moderate hearing loss, and four participants had a moderate-to-sever hearing loss. In a similar manner to Experiment I, the participants with SNHL were recruited from clients registered at the Audiology Clinic at the University of Western Ontario, Ontario, Canada. The hearing-impaired participants had symmetric and bilateral SNHL without having any other disorders (e.g. cognitive).

**Table 6-3: Audiological profile of individuals with SNHL.**

| Subject no | Age (yr)/Sex | Pure-tone average of left ear (dB HL) | Pure-tone average of right ear (dB HL) | Degree of hearing loss |
|---|---|---|---|---|
| 1 | 27/F | 38.13 | 36.25 | Mild |
| 2 | 77/M | 56.25 | 55.63 | Moderate-severe |
| 3 | 74/M | 56.25 | 58.75 | Moderate-severe |
| 4 | 80/F | 27.5 | 58.75 | Mild |
| 5 | 70/M | 48.33 | 49.38 | Moderate |
| 6 | 68/M | 71.66 | 69.44 | Moderate-severe |
| 7 | 77/M | 39.38 | 40 | Mild |
| 8 | 77/F | 44.38 | 51.25 | Moderate |
| 9 | 75/F | 26.88 | 26.25 | Mild |
| 10 | 81/M | 60 | 65.71 | Moderate-severe |

### 6.3.2 Stimuli

The noisy speech database was created for collecting the speech intelligibility data from the participants in a manner similar to Experiment I. (i.e. the clean speech sentences were taken from the HINT database). The clean speech sentences were mixed with non-stationary background noise (viz. MTBN) at different SNRs. The noisy speech stimuli were then processed by dichotic processing algorithm. Furthermore, in order to assess the benefits of the sole application of  a NR algorithm and its combination as a front-end to dichotic processing scheme, the MHA NR algorithm was applied to the noisy speech prior to the application of dichotic processing .This led to a total of 25 lists x 10 sentences/list x 4 processing condition settings (sole application of dichotic, sole application of MHA NR, combination of MHA NR and dichotic, and unprocessed) x 4 SNRs (3 dB, 0 dB, -3 dB, and -6 dB) = 4000 stimuli in the Experiment 2 database.

### 6.3.3 Results

The average scores for the NH and HI participants are shown in Figure 6 – 5 and Figure 6 – 6 , respectively. Error bars show one standard deviation of the mean. It can be noted from Figure 6 – 5 that the speech intelligibility scores for dichotic processing stimuli were better for unprocessed speech regardless of the SNR condition. However, the improvement observed was significantly less for SNR = 3, -3, and -6 dB compared to SNR = 0 dB.

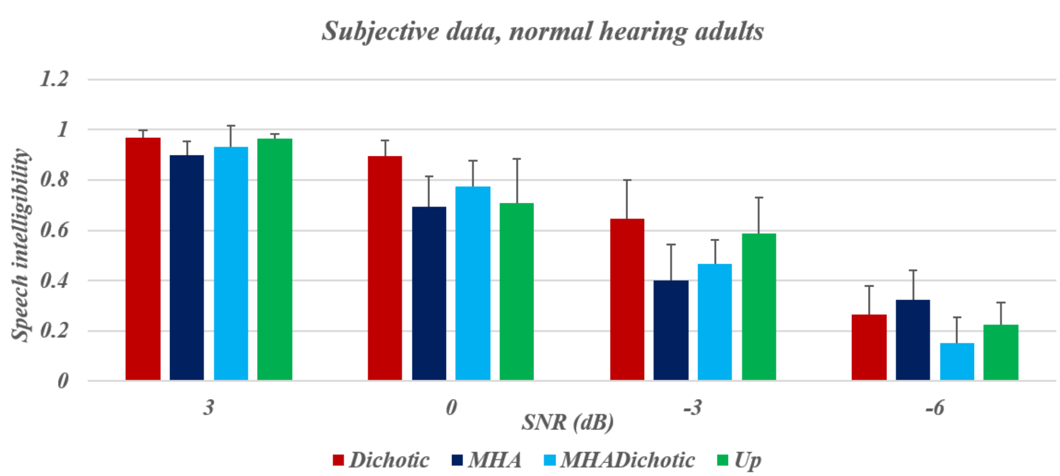



**Figure 6-5: Averaged speech intelligibility score for adults with NH.**

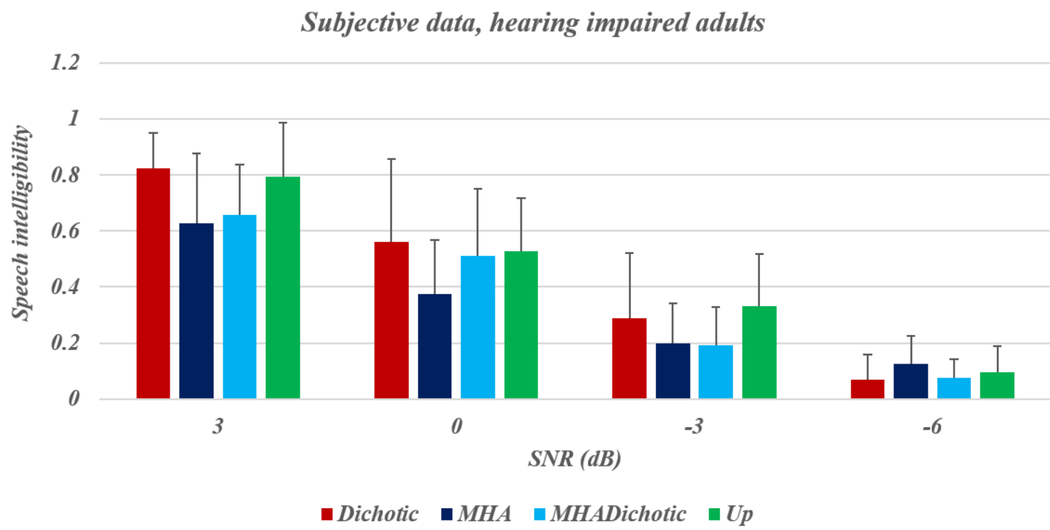



**Figure 6-6: Averaged speech intelligibility score for adults with HI.**

It can also be seen from Figure 6 – 6 that the speech intelligibility scores for dichotic processing condition were slightly higher than those for unprocessed condition for SNR = 0, 3 dB. However, the scores associated with dichotic processing were slightly lower compared to the ones associated with unprocessed conditions for SNR = -3 and -6 dB. In addition, the processing improvement observed for HI was less than the improvement observed for NH participants regardless of the SNR value. Furthermore, the sole application or incorporation of MHA NR as a front-end to dichotic processing are inferior in improving the speech intelligibility regardless of the SNR condition and participant groups. The only minor speech intelligibility improvement was observed only for a sole application of MHA NR in -6 dB SNR condition for both NH and HI participants.

#### 6.3.3.1 Statistical analysis

As the mean speech intelligibility scores differed across different SNRs and processing conditions, repeated measures ANOVA was performed on the arcsine-transformed proportion intelligibility data, with within-subjects factors, processing method (four values) and SNR (four values), and between-subject factor group status (NH or HI). Mauchly's test showed that the condition of sphericity was satisfied for processing method. However, it was violated for the SNR variable ($\chi^2(5) = 11.94$, $p = 0.036$), so the Greenhouse-Geisser correction was used for this condition ($\varepsilon = 0.768$). The results showed a significant main effects of processing method ($F\ (3, 54) = 17.75$, $p < 0.001$) and SNR ($F\ (2.3, 54) = 698.10$, $p < 0.001$) parameters. There was a significant interaction between processing method and SNR, ($F\ (9, 162) = 6.81$, $p < 0.001$), reflecting that the relative performance of the processing method depended on the SNR value. In addition, there was a significant interaction between the processing method, SNR values and the subject group (NH vs. HI) reflecting the fact that changing the processing method had a different effect across both groups. There were no other significant interactions.

Post-hoc pairwise analysis with Bonferroni correction was conducted between the NH and HI subjective data at different processing conditions and SNR values. Major outcomes of this analysis for HI participants include that (1) the scores associated with dichotic processing method were statistically similar with the ones associated with unprocessed method regardless of the SNR values. (2) the performance of dichotic processing method was significantly better than the MHA NR and the application of the MHA NR processing as a front-end to the dichotic processing method only for SNR = 3 dB respectively. (3) the scores associated with MHA NR processing method were significantly worse than unprocessed scores at SNR = 3 dB, SNR = 0 dB, and SNR = -3 dB. (4) the performance of all the processing methods was statistically similar at SNR = -6 dB.

Salient results of the post-hoc analysis for NH subjects include that (1) the scores associated with dichotic method were significantly higher than unprocessed scores only at SNR = 0 dB, (2) the performance of the MHA NR processing method was significantly worse than dichotic processing method for SNR = 3 dB and SNR = -3 dB. (3) the scores associated with unprocessed condition was significantly better that the MHA NR processing method only for SNR = -3 dB, and (4) the performance of dichotic, MHA NR and unprocessed methods were statistically similar only at SNR = -6 dB.

## 6.4 Discussion

This study contributed several novel results on the benefits of dichotic processing scheme in the presence of different types and levels of background noise for binaural hearing aid applications. In particular, this study was performed to show for what type and level of background noise, dichotic hearing can improve speech intelligibility for the HI listener. Salient experimental results are discussed in the following sections:

### 6.4.1 Subjective data

Speech intelligibility scores of individuals with SNHL were poorer when compared with those associated with NH subjects regardless of the type and level of the background noise. However, the difference between speech intelligibility scores from SNHL and NH individuals are higher for non-stationary background noise compared to scores associated with stationary background noise. Furthermore, the reduction in speech intelligibility scores with reduced SNR was higher for those who have moderate and moderate-severe degrees of HL when compared with participants, who have mild degree of HL. This may be due to difficulty in extracting the envelope and fine structure cues in adverse SNR, which is the major challenge with people with SNHL [76]. To the best of our knowledge, this study is the first one to investigate the performance of dichotic hearing for binaural hearing aid application in the presence of different types and levels of background noise at the sentence level speech perception. Overall, the results associated with this study are consistent with the results reported by Kulkarni et al. [38] , which were demonstrated that the most significant benefit of dichotic processing achieved at poorest SNR condition. In addition, the results associated with this study are in a very good agreement with previous results by Kolte and Chaudhari [44], which demonstrated that the speech perception improvement achieved by dichotic processing technique varies between subject to subject with respect to their degree of hearing loss. Furthermore, the statistical analysis results associated with this study demonstrated that the dichotic processing technique is much more effective for NH compared to HI participants, which is consistent with the more recent research study presented by Ozmeral et al. [46].

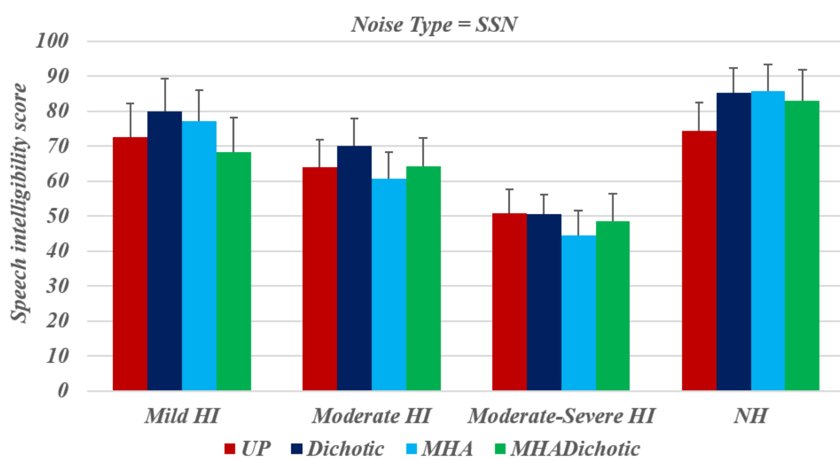



**Figure 6-7: Speech intelligibility comparison between NH and HI in the presence of SSN.**

To further shed light on the discussion in the preceding paragraph, the HI data was split based on their degree of hearing loss and shown in Figures 6-7 and 6-8. In these figures, the HI speech intelligibility data in RAUs were binned into “mild” (< 40 dB HL PTA), “moderate” (40-60 dB HL PTA), and “moderate-severe” (> 60 dB HL PTA). Consistent with the literature, these results demonstrate that the dichotic processing technique is more effective with HI individuals who have mild and moderate hearing loss when compared to HI individuals with moderate-to-severe hearing loss in the presence of stationary background noise. However, when the background noise is non-stationary, the dichotic processing technique is not effective regardless of the degree of hearing loss between HI individuals. Furthermore, the application of MHA NR by itself or the application of the MHA NR prior to the dichotic processing is inferior in improving the speech intelligibility irrespective with the degree of the hearing loss and the background noise.

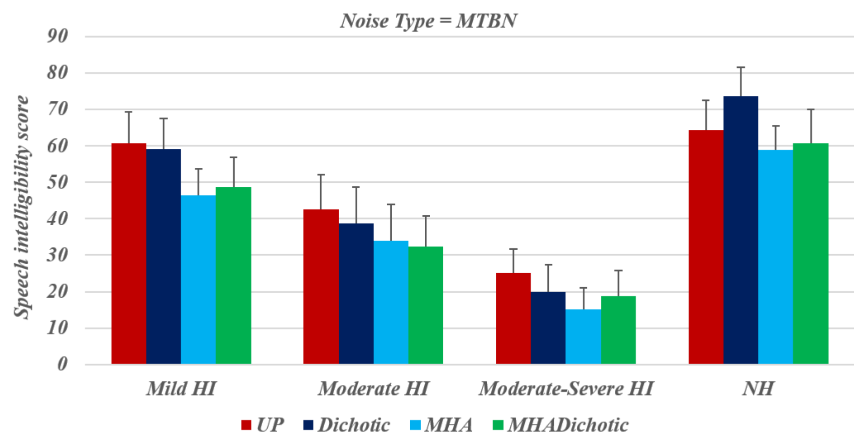



**Figure 6-8: Speech intelligibility comparison between NH and HI in the presence of MTBN.**

### 6.4.2 Dichotic processing, and interaction with noise type and SNR

This study benchmarked the performance of the dichotic hearing scheme at different noise levels and noise types. The results suggested that the performance of dichotic hearing primarily depends upon the SNR parameter and the type of the background noise. These critical parameters were not explored comprehensively in previous research [38], [42], [45]. Although dichotic processing demonstrated improvement in speech intelligibility at SNR = -3 dB for some HI participants, who have mild hearing loss, regardless of the background noise type, the results suggested that incorporating the dichotic scheme is much more beneficial for individuals with mild-moderate SNHL in the presence of stationary background noise at the poorest SNR (SNR = -6 dB). Furthermore, on average, dichotic scheme performance was not statistically better in terms of speech intelligibility when compared to the unprocessed condition when the background noise was non-stationary. However, the speech intelligibility scores associated with some HI participants, who have mild hearing loss, achieved benefits from dichotic processing in the presence of non-stationary background noise environment at SNR = 0 dB.

### 6.4.3 Effect of the MHA NR algorithm

Statistical results demonstrated that the performance of the MHA NR was statistically worse compared to unprocessed condition in terms of speech intelligibility for stationary background noise at SNR = 3 dB for HI participants. In addition, the performance of the MHA NR was not statistically better in terms of intelligibility compared to unprocessed condition in the presence of stationary background noise at SNR = 0, -3, and -6 dB for HI subjects. Furthermore, when the background noise is non-stationary, the performance of the MHA NR was significantly poorer at SNR = 3, 0, -3 dB and statistically similar at SNR = -6 dB compared to unprocessed condition for HI participants. These results are in a good agreement with the results obtained in [77], [78], and [76], which demonstrated that NR algorithm alone does not improve intelligibility for HI individuals in various noisy conditions.

### 6.4.4 Dichotic processing, and interaction with MHA NR algorithm

Statistical results indicate that the incorporation of the MHA NR as a front-end to the application of dichotic hearing was not beneficial to improve the effectiveness of the dichotic processing performance regardless of the type and level of the background noise. This may be defended by the fact that musical noise generated with MHA NR can reduce the modulation depth and create spurious modulations to the speech signal. Hence, since individuals with SNHL suffer from deficits such as frequency selectivity or impaired modulation detection, incorporating the MHA NR as a front-end to dichotic processing may increase their spectral masking thresholds. However, it will be of future research interest to investigate a combined directional microphone processing NR system as a front-end to the application of dichotic scheme in order to further investigate the impact of noise on dichotic processing. Although, previous research work by Kulkarni [38] reported no significant effect on the identification of the direction of broadband sound sources achieved by incorporating binaural dichotic processing, it should be beneficial to investigate the impact of dichotic processing technique on the identification of sound sources at different types of broadband noisy stimuli as a possible future research interest.

Generally, the subjective experimental results demonstrated in this research study are worthwhile in developing the realtime application of the dichotic processing for binaural hearing aid applications. It is evident from the subjective results that the dichotic processing should be applied in binaural hearing aids by deactivating the digital NR algorithm of the hearing aid regardless of the noise level and type. It is also evident from the subjective results that the main benefit from dichotic processing technique is accrued when the SNR is poor (e.g. SNR = -6 dB) and when the background noise is stationary. This outcome recommends that depending on the type of processing condition, dichotic scheme should be activated as modern hearing aids incorporate automatic environment classification algorithms, which estimate the type and level of background noise to be used in decision making on the activation of the algorithms.

## 6.5 Summary

This chapter portrayed the performance of the dichotic hearing processing for binaural hearing aid applications. In particular, subjective experiments were conducted to investigate the performance of the dichotic hearing scheme in terms of speech intelligibility at different types and levels of background noise. Key new results from this study include: (1) the dichotic hearing scheme is effective only in certain background noise as well as SNR conditions, and (2) the incorporation of the MHA NR algorithm as a front-end to the application of dichotic hearing processing is not beneficial in improving the speech intelligibility regardless of the subjective groups and processing conditions. In conclusion, dichotic hearing processing can be considered for improving the speech intelligibility for individuals with SNHL in some environmental conditions by reducing the spectral masking thresholds due to the fact that sensory cells corresponding to alternate bands are always relaxed in spectral splitting scheme. The next Chapter concludes the research studies presented in this thesis followed by proposing some possible future works.

# Chapter 7

# 7 Summary

This chapter will present an overview of the presented work with a particular focus on the key contributions and proposed future work.

## 7.1 Thesis summary

Previous studies have shown that exaggerating the slow temporal modulations, which is achieved by applying different schemes of EE algorithms, demonstrated benefits on phrase and consonant identification for individuals with ANSD. In addition, published studies demonstrated that enhancing both the spectral and temporal contrast, which is achieved by incorporating the companding algorithm, improved speech perception in individuals with ANSD. Furthermore, past studies also demonstrated that dichotic hearing processing technique improved speech intelligibility for individuals with SNHL by reducing the spectral masking threshold and improving the frequency selectivity for patients who are suffering from SNHL.

Although results associated with previous research studies are promising, comprehensive assessments of the above signal processing techniques in more realistic noisy environments are lacking. Therefore, this thesis contributed novel results on the performance of the alternative class of signal processing techniques, which are effective in improving speech intelligibility with individuals who have poor temporal and/ or spectral processing as indicated in the following paragraph.

The main objectives of this thesis concentrate on the comprehensive assessment of two different schemes of EE algorithms (e.g. dynamic EE and static EE) by children with APD in a variety of noisy conditions. In addition, reference-free and full-reference objective speech intelligibility predictors were developed based on HASPI and ModA metrics, respectively and utilized for the assessment of EE algorithms. Furthermore, in this thesis the comprehensive evaluation of dichotic processing in the presence of different types and levels of background noise was examined with individuals with SNHL.

Chapter 2 presented published results on the effectiveness of various signal processing algorithms (e.g. EE, companding, and dichotic) followed by an individual description of each algorithm. In addition, a literature review of the existing portable platforms for implementing signal processing algorithms was examined as well as the description of iPad and open MHA platforms. Furthermore, an intrusive (i.e. HASPI) and non-intrusive (i.e. ModA) objective metrics were described followed by introducing the well-known NR algorithms (e.g. logMMSE and MHA NR).

In Chapter 3, the performance of the dynamic EE algorithm was conducted for remote microphone applications across different types and levels of background noise. The assessment of the algorithm was performed in children suspected with APD in terms of speech intelligibility in the presence of stationary background noise at the listener location. An intrusive objective speech intelligibility predictor based on HASPI was developed (DEEDT) and utilized for the comprehensive assessment of the dynamic EE algorithms across a variety noisy conditions. The subjective and objective assessments of dynamic EE suggested that the dynamic EE algorithm is more suited for RM applications, wherein the SSNR is high (e.g.  3 dB) and LSNR is poor (e.g.= -6 dB).

The focus of Chapter 4 was on the evaluation of the static EE for hearing aid applications by performing both subjective and objective experiments. The subjective assessment of the static EE algorithm was conducted in the presence of stationary and non-stationary background noise in children with APD. For objective evaluation of the static EE, an intrusive objective intelligibility model based on HASPI was developed (i.e. SEEDT) and utilized for further benchmarking of the EE algorithms. Experimental results demonstrated that the application of static EE for hearing aid applications is more beneficial only when the SNR is poor, and the background noise is stationary.

In Chapter 5, the robustness of individual DEEDT and SEEDT objective predictors was evaluated by testing with APD subjective scores, which were collected from static EE and dynamic EE , respectively. In addition, generalized versions of intrusive and non-intrusive objective models (e.g. MHASPI and WModA) were derived to predict the speech intelligibility of novel EE algorithms regardless of the type of background noise. Furthermore, companding architecture was studied and examined, and it was assessed objectively using non-intrusive generalized model (i.e. WModA) across different types and levels of background noise.

In Chapter 6, the effectiveness of the dichotic hearing scheme was investigated with individuals with HI in terms of speech intelligibility. Subjective experiments were conducted in the presence of different types and levels of background noise.  Subjective results revealed that the application of dichotic processing is mainly beneficial for poorest SNR (e.g. SNR = -6 dB) when the background noise is stationary.

## 7.2 Key contributions

### 7.2.1 Chapter 3

1) This study demonstrated the benefits of the dynamic EE on sentence-level speech perception in children with suspected APD.

2) It was shown that the dynamic EE algorithm is effective in terms of speech intelligibility only in certain combinations of source and listener SNR conditions for RM applications.

3) It was demonstrated that the incorporation of NR algorithms can expand the range of SNRs over which the dynamic EE are effective.

4) The development of an intrusive objective predictor (DEEDT) based on HASPI metric was presented for predicting APD subjective scores associated with dynamic EE.

### 7.2.2 Chapter 4

1) This study demonstrated the effectiveness of the static EE on sentence-level speech perception in children with APD across different types and levels of background noise for hearing aid applications.

2) It was demonstrated that the static EE is less effective for children with APD in improving their speech perception in non-stationary noisy environments when compared to stationary noisy environments.

3) It was shown that incorporation of the MHA NR algorithm as a front-end to the application of the static EE algorithm is beneficial only for the poorest SNR condition when the background noise is stationary.

4) It was shown that the application of the logMMSE NR algorithm prior to the static EE is not beneficial regardless of the noise type and processing condition.

5) The development of an intrusive objective predictor (SEEDT) based on HASPI was presented, which will be used for predicting APD subjective scores associated with novel EE algorithms.

### 7.2.3 Chapter 5

1) The development of generalized intrusive (MHASPI) and non-intrusive (WModA) objective models based on HASPI and ModA respectively was presented.

2) The robustness of both MHASPI and WModA models was evaluated by testing with APD subjective scores.

3) The assessment of the companding algorithm was presented using the generalized non-intrusive objective model (WModA).

### 7.2.4 Chapter 6

1) A new filterbank architecture was used for the implementation of the binaural dichotic processing and evaluated with HI listeners in a number of noisy environments.

2) This study demonstrated the effectiveness of the dichotic processing scheme with individuals with SNHL in the presence of different types and levels of background noise for binaural hearing aid applications.

3) It was demonstrated that the dichotic hearing scheme was more effective for individuals with SNHL in improving their speech intelligibility in stationary background noise when compared to non-stationary background noise.

4) It was shown that the application of the MHA NR algorithm as a front-end to the application of dichotic processing is not beneficial in improving the speech intelligibility regardless of the noise type and processing condition.

## 7.3 Study limitations

1) The performance of the signal processing algorithms was evaluated using one speech database, *viz.* the Hearing in Noise Test (HINT) database. The HINT database contains sentences spoken by a single male talker, and the number of correctly repeated words in each sentence was scored in the subjective evaluation. For greater generalizability of the algorithm performance in real world applications, additional subjective experiments with databases incorporating speech samples from a diverse set of male and female talkers are warranted.

2) The performance of the signal processing algorithms was assessed in the presence of two types of background noise: stationary speech-shaped noise and non-stationary multi-talker babble. Once again, for generalization to real word environments, the performance of algorithms must be evaluated in environments with additional types of background noise and different degrees of reverberation. In this context, evaluation of the algorithms in the field by potential users would greatly increase the ecological validity of the algorithm performance.

3) The behavioural assessment of the signal processing algorithms was carried out for certain processing algorithms. In addition, the chosen algorithms were evaluated with a few choices of their tunable parameters. In part, this was due to the limited number of sentence lists in the HINT database, which restricted the number of processing algorithm and parameter combinations that could be assessed. Access to larger databases with a diverse set of male and female speech samples will allow for more comprehensive benchmarking of a broader range of processing settings.

4) A primary concern for the proposed data-driven model is its generalizability and applicability to unseen data. In this thesis, these important features were only tested on a certain algorithm (i.e. companding). However, for real world application, the generalizability and applicability of the proposed intrusive and non-intrusive objective models must be validated with additional behavioural data collected with different implementations of the envelope enhancement algorithms.

## 7.4 Future work

### 7.4.1 Realtime implementation

The successful subjective and/or objective offline evaluations of the discussed signal processing algorithms in this thesis provide the motivation for realtime implementation of these algorithms for future work. However, the realtime implementation may not be feasible (e.g. the offline implementation is not causal). Hence, implementation of discussed algorithms would require modifications to the processing schemes as discussed in the following sections. It is pertinent to point out that OpenMHA platform is proposed for realtime implementation of these signal processing algorithms.

#### 7.4.1.1 Dynamic EE and companding

In this research study, zero-phase filtering approach was used to implement the filterbanks for offline processing of both dynamic EE and companding algorithms. However, zero-phase filtering technique, which relies on non-causal processing, is not practical for realtime implementations of these algorithms. Hence, alternative approaches recommended by Clarkson and Bhagat [62] and Koutsogiannaki et al [63] should be considered for realtime implementation of these algorithms. In addition, another important issue to be considered for realtime implementation of dynamic EE algorithm is choosing the proper value for minimum envelope value, $E_{min}$. This value has to be updated for each frequency band or it has to be assumed as zero. Furthermore, the value of exponential time constant, $\tau$ must be chosen carefully as this value determines how much $k$ will fluctuate as the signal amplitude varies from its maximum to minimum values. The last important issue for realtime implementation of dynamic EE algorithm is that the users can access to control and adjust minimum and maximum power of expansion, $k$, as well as the exponential time constant, $\tau$ to adjust the algorithm based on their individual needs and hearing impairments. For the companding algorithm, it may be beneficial once again for the users to adjust and tune the filter parameters, $q_1$ and $q_2$, and the expansion/compression coefficients, $n_1$ and $n_2$ for their individual needs and speech environments.

#### 7.4.1.2 Static EE

The offline implementation of the static EE was designed based on non-zero phase filtering approach. Hence, there are fewer issues to contend for realtime implementation of this algorithm. However, once again, it may be worthwhile for the users to adjust and tune the algorithm parameters, enhancement value, slow and fast modulation rates, with respect to their individual deficits and background noise environment. Furthermore, it may be beneficial to implement the static EE algorithm based on the analysis-synthesis system using a Gammatone filterbank in a manner similar to the dichotic processing implementation. Subjective and objective evaluations of the modified version of the static EE algorithm are motivated to demonstrate the performance comparison between Bark-scale and Gammatone filterbank implementations.

#### 7.4.1.3 Dichotic processing

Previous research [36] and [35] implemented the dichotic processing scheme in realtime on TMS 320c25 signal processor. Therefore, realtime implementation of this algorithm should be feasible on OpenMHA platform. However, it should be beneficial to demonstrate the impacts of modification of filter parameters on speech quality, intelligibility, and source localization. In addition, it should be worthwhile to investigate the effectiveness of this technique in improving the speech intelligibility of children with APD in the presence of different noisy environments.

### 7.4.2 Algorithm Parameter Customization

All the above algorithms have tunable parameters and currently there is no guidance on how to set these parameters. For example, for EE and companding algorithms, the parameters should be customized in relation to their deficits level in temporal and/ or spectral processing. For the dichotic processing scheme, the algorithm parameters should be customized based on degree of hearing loss in individuals with SNHL. Hence, another possible future work could be customizing the parameters of these algorithms either through the simplex procedure or using the genetic algorithm.

# Bibliography


[1] H. Dillon, *Hearing Aids*, 2nd ed. Boomerang Press, 2012.

[2] ASHA, "(Central) Auditory Processing Disorders," 2005.

[3] S. M. Kim and S. Bleeck, "An open development platform for auditory real-time signal processing," *Speech Commun.*, vol. 98, pp. 73–84, 2018.

[4] T. H. Falk, C. X. Zheng, and W.-Y. Chan, "A Non-Intrusive Quality and Intelligibillity Measure of Reverberant and Dereverberated Speech," *IEEE Trans. Audio,Speech, Lang. Process.*, vol. 18, no. 7, pp. 1766–1774, 2010.

[5] B. Morgan, "Development and Evaluation of Envelope, Spectral and Time Enhancement Algorithms for Auditory Neuropathy," Western University, 2011.

[6] C. J. Plack, *The Sense of Hearing*, 2'nd. Psychology Press, 2014.

[7] S. Flanagan, T. Zorila, S. Yannis, and B. C. J. Moor, "Speech Processing to Improve the Perception of Speech in Background Noise for Children with Auditory Processing Disorder and Typically Developing Peers," *Trends Hear.*, vol. 22, pp. 1–8, 2018.

[8] G. Rance, "Auditory Processing in Individuals with Auditory Neuropathy Spectrum Disorder," in *Auditory Processing Disorders: Assessment, Management and Treatment*, D. Geffner and D. R. Swain, Eds. 2013, pp. 185–210.

[9] J. R. Lucker, "The History of Auditory Processing Disorders in Children," in *Auditory Processing Disorders: Assessment, Management and Treatment*, D. Geffner and D. R. Swain, Eds. 2013, pp. 33–58.

[10] V. K. Narne and C. S. Vanaja, "Perception of Speech with Envelope Enhancement in Individuals with Auditory Neuropathy and Simulated Loss of Temporal Modulation Processing," *Int. J. Audiol.*, vol. 48, no. 10, pp. 700–707, 2009.

[11] F. Zeng, "Auditory Neuropathy:why Some Hearing-Impaired Listerens can Hear but do not Understand and how can DSP Technology help them," in *IEEE signal processing society*, 2000.

[12] I. Berlin, L. Hood, and T. Morlet, "Multi-site Diagnosis and Management of 260 Patients with

Auditory Neuropathy/Dys-Synchrony (Auditory Neuropathy Spectrum Disorder),” *Int. J. Audiol.*, vol. 49, pp. 30–43, 2010.

[13] V. Hamacher *et al.*, “Signal Processing in High-End Hearing Aids: State of the Art, Challenges, and Future Trends,” *EURASIP J. Adv. Signal Process.*, vol. 18, no. 1687–6180, pp. 2915–2929, 2005.

[14] P. Trautwein, J. Shallop, L. Fabry, and R. Freidman, “Cochlear Implementation of Patients with Auditory Neuropathy,” in Auditory Neuropathy: a New Perspective on Hearing Disorders,” *Singul. Thomson Learn.*, pp. 203–232, 2001.

[15] W. Gstoettner *et al.*, “Cochlear Implant Deep Electrode Insertion: Extent of Insertional Trauma,” *Acta Otolaryngol.*, vol. 117, no. 2, pp. 274–277, 1997.

[16] S. VR, M. R, N. A, M. A, and S. DK, “Cochlear Implants and Auditory Neuropathy Spectrum Disorder,” *Pediatr Neonatal Nurs Open Access*, vol. 1.2, no. 2470-0983, pp. 1–4, 2015.

[17] J. H. Hwang *et al.*, “Effects of the Simultaneous Application of Nonlinear Frequency Compression and Dichotic Hearing on the Speech Recognition of Severely Hearing-Impaired Subjects: Simulation Test,” *Clin Exp Otorhinolaryngol*, vol. 8, no. 2, pp. 102–110, 2015.

[18] M. J. Pottackal and S. Appu, “Perception of Hearing Aid- Processing Speech in Individuals with Late-Onset Auditory Neuropathy Spectrum Disorder,” *J. Am. Acad. Audiol.*, vol. 26, no. 10, pp. 815–823, 2015.

[19] E. Walker, R. McCreery, M. Spratford, and P. Roush, “Children with Auditory Neuropathy Spectrum Disorder Fitted with Hearing Aids Applying the American Academy of Audiology Pediatric Amplification Guideline: Current Practice and Outcomes,” *J. Am. Acad. Audiol.*, vol. 27, no. 3, pp. 204–218, 2016.

[20] F. Kuk, “Hearing Aids for Children with Auditory Processing Disorders?,” *Semin. Hear.*, vol. 32, no. 2, pp. 189–195, 2011.

[21] E. C. Schafer *et al.*, “A Critical Review of Remote-Microphone Technology for Children with Normal Hearing and Auditory Differences,” *J. Educ. Audiol.*, vol. 20, pp. 1–11, 2014.

[22] G. Rance, “Auditory Neuropathy/Dys-synchrony and Its Perceptual Consequences,” *Trends Hear.*, vol. 9, no. 1, pp. 1–43, 2005.

[23] S. Reynolds, H. M. Kuhaneck, and B. Pfeiffer, “Systematic Review of the Effectivness of Frequency Modulation Devices in Improving Academic Outcomes in Children with Auditory Processing Difficulties,” *Am. J. Occup. Ther.*, vol. 70, pp. 1–11, 2015.

[24] V. K. Narne and C. S. Vanaja, “Effect of Envelope Enhancement on Speech Perception in Individuals with Auditory Neuropathy,” *Ear Hear.*, vol. 29, no. 1, pp. 45–53, 2008.

[25] V. K. Narne and C. S. Vanaja, “Perception of Envelope-Enhanced Speech in the Presence of Noise by Individuals with Auditory Neuropathy,” *Ear Hear.*, vol. 30, no. 1, pp. 136–142, 2009.

[26] H. N. Shetty and V. Kooknoor, “Recognition of Deep Band Modulation Consonants in Quiet and Noise in Older Individulas with and without Hearing Loss,” *Int. Adv. Otol.*, vol. 12, no. 3, pp. 282–289, 2016.

[27] H. N. Shetty and V. Kooknoor, “Deep Band Modulated Phrase Perception in Quiet and Noise in Individuals with Auditory Neuropathy Spectrum Disorder and Sensorineural Hearing Loss,” *Noise&Health*, vol. 19, no. 89, pp. 174–182, 2017.

[28] M. Nilsson, S. D. Soli, and J. A. Sulivan, “Development of the Hearing in Noise Test for the Measurement of Speech Reception Thresholds in Quiet and in Noise,” *Acoust. Soc. Am.*, vol. 95, no. 2, pp. 1085–1099, 1994.

[29] C. H. Taal, R. C. Hendriks, and R. Heusdens, “A Short-Time Objective Intelligibility Measure for Time-Frequency Weighted Noisy Speech,” in *Conference on Acoustics, Speech, and Signal Processing*, 2010, pp. 4214–4217.

[30] J. Kates and K. Arehart, “The Hearing Aid Speech Perception Index (HASPI),” *Speech Commun.*, pp. 75–93, 2014.

[31] F. Chen, O. Hazrati, and P. C. Loizou, “Predicting the Intelligibility of Reverberant Speech for Cochlear Implant listeners with a Non-Intrusive Intelligibility Measure,” *Biomed. Signal Process. Control*, vol. 8, no. 3, pp. 311–314, 2013.

[32] L. Turicchia and R. Sarpeshkasr, “A Bio-Inspired Companding Strategy for Spectral Enhancement,” *IEEE Trans Acoust Speech Signal Process*, vol. 13, no. 2, pp. 243–253, 2005.

[33] F. Zeng and A. Bhattacharya, “Companding to Improve Cochlear-Implant Speech Recognition in

Speech-Shaped Noise," *Acoust. Soc. Am.*, vol. 122, no. 2, pp. 1079–1089, 2007.

[34] V. Narne and A. Barman, "Effect of Companding on Speech Recognition in Quiet and Noise for Listeners with ANSD," *Int. J. Audiol.*, vol. 53, pp. 94–100, 2014.

[35] T. Lunner, S. Arlinger, and J. Hellgren, "8-channel Digital Filter Bank for Hearing Aid use: Preliminary Results in Monaural, Diotic, and Dichotic Modes," *Scand Audiol Suppl*, vol. 38, pp. 75–81, 1993.

[36] D. S. Chaudhari and P. C. Pandey, "Critical Band Splitting of Speech Signal for Reducing the Effect of Spectral Masking in Bilateral Sensorineural Hearing Impairment," in *5th Int Symp Signal Proc and Its Applications (ISSPA 1999)*, 1999, pp. 119–122.

[37] Alice, N. Cheeran, and P. C. Pandey, "Evaluation of Speech Processing Schemes using Binaural Dichotic Presentation to Reduce the Effect of Masking in Hearing-Impaired Listeneres," in *18th Int Congress Acoustics , Kyoto, Japan, II*, 2004, pp. 1523–1526.

[38] N. Kulkarni, C. Pandey, and S. Jangamashetti, "Binaural Dichotic Presentation to Reduce the Effects of Spectral Masking in Moderate Bilateral Sensorineural Hearing Loss," *Int. J. Audiol.*, vol. 51, no. 4, pp. 334–344, 2012.

[39] S. S. Nagarajan, X. Wang, and M. M. Merzenich, "Speech Modification Algorithms Used for Training Language Learning-Impaired Children," *IEEE Trans. Rehabilation Eng.*, vol. 6, no. 3, pp. 257–268, 1998.

[40] J. Mathai and A. Yathiraj, "Effect of Temporal Modification and Vowel Context on Speech Perception in Individuals with Auditory Neuropathy Spectrum Disorder (ANSD)," *Hear. Balanc. Commun.*, vol. 11, no. 4, pp. 198–207, 2013.

[41] F. Zeng and A. Bhattacharya, "Companding to Improve Cochlear Implant Speech Recognition in Speech Shaped Noise," *J. Acoust. Soc. Am.*, vol. 122, no. 2, pp. 1079–1089, 2007.

[42] D. S. Chaudhari and P. C. Pandey, "Dichotic Presentation of Speech Signal Using Critical Filter Bank for Bilateral Sensorineural Hearing Impairment," *J. Acoust. Soc. Am.*, vol. 1, pp. 213–214, 1998.

[43] A. Murase, F. Nakajima, S. Sakamoto, Y. Suzuki, and T. Kawase, "Effect and Sound Localization

with Dichotic-Listening Digital Hearing Aids," in *International Congresses on Acoustics*, 2004, pp. 1519–1522.

[44] M. T. Kolte and D. S. Chaudhari, "Evaluation of Speech Processing Schemes to Improve Perception of Sensorineural Hearing Impaired," *Curr. Sci.*, vol. 98, no. 5, pp. 613–615, 2010.

[45] A. Mani, P. C. Loizou, A. Shoup, P. Roland, and P. Kruger, "Dichotic Speech Recognition by Bilateral Cochlear Implant Users," *Int. Congr. Ser.*, vol. 1273, pp. 466–469, 2004.

[46] E. J. Ozmeral, E. Buss, and J. W. Ha, "The Effects of Sensorineural HearingImpairment on Asynchronous Glimpsingof Speech," *PLoS One*, vol. 11, no. 5, pp. 1–18, 2016.

[47] N. Magotra and S. Sirivara, "Real-Time Digital Speech Processing Strategies for the Hearing Impaired," in *Acoustics, Speech and Signal Processing*, 1997, vol. 2, no. 1520–6149, pp. 1211–1214.

[48] T. Stetzler, N. Magotra, P. Gelabert, P. Kasthuri, and S. Bangalore, "Low Power Real-Time Programmable DSP Development Platform for Digital Hearing Aids," in *Acoustics, Speech, and Signal Processing*, 1999, no. 1520–6149, pp. 2339–2342.

[49] U. Rass and G. H. Steeger, "Evaluation of Digital Hearing Aid Algorithms on Wearable Signal Processor Systems," in *8th Europen Signal Processing (EUSIPCO)*, 1996, pp. 475–478.

[50] U. Rass and G. H. Steeger, "A High Performance Pocket-Size System for Evaluation in Acoustic Signal Processing," *EURASIP J. Appl. Signal Processing*, vol. 2001, no. 3, pp. 163–168, 2001.

[51] H. Kruger, T. Lotter, G. Enzner, and P. Vary, "A PC Based Platform for Multichannel Real-Time Audio Processing," in *International Workshop on Acoustic Echo and Noise Control (IWAENC)*, 2003.

[52] A. Amlani, B. Taylor, C. Levy, and R. Robbins, "Utility of Smartphone-Based Hearing Aid Applications as a Substitute to Traditional Hearing Aids," *Hear. Rev.*, no. December, 2013.

[53] G. Grimm, T. Herzke, D. Berg, and V. Hohmann, "The Master Hearing Aid : A PC-Based Platform for Algorithm Development and Evaluation," *Acta Acust. United with Acust.*, vol. 92, no. 4, pp. 618–628, 2006.

[54] G. Paya-Vaya, H. Blume, T. Herzke, and V. Hohmann, “A Mobile soC-based Platform for Evaluating Hearing Aid Algorithms and Architectures,” in *Consumer Electronics-Berlin(ICCE-Berlin)*, 2015, pp. 93–97.

[55] “Accelerate VDSP Library.” [Online]. Available: https://developer.apple.com/documentation/accelerate/vdsp.

[56] H. GGmbh, “The Open Master Hearing Aid (Opne MHA).”

[57] “Intel Integrated Performance Primitive,” 2015.

[58] J. M. Kates, K. H. Arehart, M. C. Anderson, K. Muralimanohar, and L. O. Harvey, “Using Objective Metrics to Measure Hearing Aid Performance,” *Ear Hear.*, vol. 39, no. 6, pp. 1165–1175, 2018.

[59] P. C. Loizou, *Speech Enhancement : Theory and Practice*, Second. 2013.

[60] C. Breithaupt, T. Gerkmann, and R. Martin, “A Novel A Priori SNR Estimation Approach Based on Selective Cepstro-Temporal Smoothing,” in *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2008, pp. 4897–4900.

[61] Y. Ephraim and D. Malah, “Speech Enhancement Using a Minimum-Mean Squar Error Short-Time Spectral Amplitude Estimator,” *IEEE Trans. Acoust.*, vol. 32, no. 6, pp. 1109–1121, 1984.

[62] P. M. Clarkson and S. Bahgat, “Real-Time Speech Enhancement System using Envelope Expansion Technique,” *Electron. Lett.*, vol. 25, no. 17, pp. 1186–1188, 1989.

[63] M. Koutsogiannaki, H. Francois, K. Choo, and E. Oh, “Real-Time Modulation Enhancement of Temporal Envelopes for Increasing Speech Intelligibility,” in *Interspeech*, 2017, pp. 1973–1977.

[64] ASHA, “Central Auditory Processing Disorders,” 2005. [Online]. Available: http://www.asha.org/docs/html/tr2005-00043.html.

[65] G. A. Studebaker, “A Rationalized Arcsine Transform,” *J. Speech, Lang. Hear. Res.*, vol. 28, no. 3, pp. 455–462, 1985.

[66] Y. Hu and P. C. Loizou, “Evaluation of Objective Quality Measures for Speech Enhancement,” *IEEE Trans. Audio. Speech. Lang. Processing*, vol. 16, no. 1, pp. 229–238, 2008.

[67] A. J. Myles, R. N. Feudale, Y. Liu, N. A. Woody, and S. D. Brown, “An Introduction to Decision Tree Modeling,” *J. Chemom.*, vol. 18, pp. 275–285, 2004.

[68] S. D. Soli *et al.*, “Evidence-Based Occupational Hearing Screening II: Validation of a Screening Methodology using Measures of Functional Hearing Ability,” *Int. J. Audiol.*, vol. 57, pp. 323–334, 2018.

[69] A. J. Vermiglio, “The American English Hearing in Noise Test,” *Int. J. Audiol.*, vol. 47, no. 6, pp. 386–387, 2008.

[70] J. M. Kates, “Modeling the Effects of Single-Microphone Noise-Suppression,” *Speech Commun.*, vol. 90, pp. 15–25, 2017.

[71] S.-H. Jin and C. Liu, “English Sentence Recognition in Speech-Shaped Noise and Multi-Talker Babble for English- Chinese-, and Korean-Native Listeners,” *J. Acoust. Soc. Am.*, vol. 132, no. 5, pp. 391–397, 2012.

[72] P. Allen and C. Allan, “Auditory processing disorders: Relationship to cognitive processes and underlying auditory neural integrity,” *Int. J. Pediatr. Otorhinolaryngol.*, vol. 78, pp. 198–208, 2014.

[73] M. Kuhn and K. Johnson, *Applied Predictive Modeling*, 1 st. Springer, 2013.

[74] V. Hohmann, “Frequency Analysis and Synthesis using a Gammatone Filterbank,” *Acta Acust. united with Acust.*, vol. 88, no. 3, pp. 433–442, 2002.

[75] S. Scollie *et al.*, “The Desired Sensation Level Multistage Input/Output Algorithm,” *Trends Amplif.*, vol. 9, no. 4, pp. 159–197, 2005.

[76] Raphael Koning, “Perceptual and Model-Based Evaluation of Ideal Time-Frequency Noise Reduction in Hearing-Impaired Listeners,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 3, 2018.

[77] Y. Hu and P. C. Loizou, “A Comparative Intelligibility Study of Single-Microphone Noise Reduction Algorithms,” *J. Acoust. Soc. Am.*, vol. 122, no. 3, pp. 1777–1786, 2007.

[78] I. Brons, R. Houben, and W. A. Dreschler, “Effects of Noise Reduction on Speech Intelligibility, Perceived Listening Effort, and Personal Preference in Hearing-Impaired Listeners,” *Trends Hear.*, vol. 18, pp. 1–10, 2014.

# Appendix A: Dynamic EE Speech Intelligibility Statistical Report

## General Linear Model

**Notes**

| | | |
|---|---|---|
| Output Created | | 07-JUL-2018 14:09:59 |
| Comments | | |
| Input | Data | \\myfiles.uwo.pri\vparsa\Documents\sAPDnNHChildrenRAUs.sav |
| | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 23 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing. |
| | Cases Used | Statistics are based on all cases with valid data for all variables in the model. |

| | | |
|---|---|---|
| Syntax | | GLM tau1SNR3 tau1SNR0 tau1SNRm3 tau1SNRm6 tau2SNR3 tau2SNR0 tau2SNRm3 tau2SNRm6 tau3SNR3 tau3SNR0<br><br>tau3SNRm3 tau3SNRm6 notauSNR3 notauSNR0 notauSNRm3 notauSNRm6 BY Group<br><br>/WSFACTOR=tau 4 Polynomial SNR 4 Polynomial<br><br>/METHOD=SSTYPE(3)<br><br>/PRINT=ETASQ<br><br>/CRITERIA=ALPHA(.05)<br><br>/WSDESIGN=tau SNR tau*SNR<br><br>/DESIGN=Group. |
| Resources | Processor Time | 00:00:00.02 |
| | Elapsed Time | 00:00:00.02 |

[DataSet1] \\myfiles.uwo.pri\vparsa\Documents\sAPDnNHChildrenRAUs.sav

**Within-Subjects Factors**

Measure: MEASURE_1

| tau | SNR | Dependent Variable |
|---|---|---|
| 1 | 1 | tau1SNR3 |
| | 2 | tau1SNR0 |
| | 3 | tau1SNRm3 |
| | 4 | tau1SNRm6 |
| 2 | 1 | tau2SNR3 |
| | 2 | tau2SNR0 |
| | 3 | tau2SNRm3 |
| | 4 | tau2SNRm6 |
| 3 | 1 | tau3SNR3 |
| | 2 | tau3SNR0 |
| | 3 | tau3SNRm3 |
| | 4 | tau3SNRm6 |
| 4 | 1 | notauSNR3 |
| | 2 | notauSNR0 |
| | 3 | notauSNRm3 |
| | 4 | notauSNRm6 |

**Between-Subjects Factors**

| | | N |
|---|---|---|
| 1 = sAPD; 2 = Normal | 1.00 | 11 |
| | 2.00 | 12 |

**Multivariate Tests[a]**

| Effect | | Value | F | Hypothesis df | Error df | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|---|
| tau | Pillai's Trace | .965 | 172.675[b] | 3.000 | 19.000 | .000 | .965 |
| | Wilks' Lambda | .035 | 172.675[b] | 3.000 | 19.000 | .000 | .965 |
| | Hotelling's Trace | 27.265 | 172.675[b] | 3.000 | 19.000 | .000 | .965 |
| | Roy's Largest Root | 27.265 | 172.675[b] | 3.000 | 19.000 | .000 | .965 |
| tau * Group | Pillai's Trace | .207 | 1.651[b] | 3.000 | 19.000 | .211 | .207 |
| | Wilks' Lambda | .793 | 1.651[b] | 3.000 | 19.000 | .211 | .207 |
| | Hotelling's Trace | .261 | 1.651[b] | 3.000 | 19.000 | .211 | .207 |
| | Roy's Largest Root | .261 | 1.651[b] | 3.000 | 19.000 | .211 | .207 |
| SNR | Pillai's Trace | .974 | 237.355[b] | 3.000 | 19.000 | .000 | .974 |
| | Wilks' Lambda | .026 | 237.355[b] | 3.000 | 19.000 | .000 | .974 |
| | Hotelling's Trace | 37.477 | 237.355[b] | 3.000 | 19.000 | .000 | .974 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Roy's Largest Root | 37.477 | 237.355[b] | 3.000 | 19.000 | .000 | .974 |
| SNR * Group | Pillai's Trace | .313 | 2.880[b] | 3.000 | 19.000 | .063 | .313 |
| | Wilks' Lambda | .687 | 2.880[b] | 3.000 | 19.000 | .063 | .313 |
| | Hotelling's Trace | .455 | 2.880[b] | 3.000 | 19.000 | .063 | .313 |
| | Roy's Largest Root | .455 | 2.880[b] | 3.000 | 19.000 | .063 | .313 |
| tau * SNR | Pillai's Trace | .961 | 35.288[b] | 9.000 | 13.000 | .000 | .961 |
| | Wilks' Lambda | .039 | 35.288[b] | 9.000 | 13.000 | .000 | .961 |
| | Hotelling's Trace | 24.430 | 35.288[b] | 9.000 | 13.000 | .000 | .961 |
| | Roy's Largest Root | 24.430 | 35.288[b] | 9.000 | 13.000 | .000 | .961 |
| tau * SNR * Group | Pillai's Trace | .471 | 1.285[b] | 9.000 | 13.000 | .330 | .471 |
| | Wilks' Lambda | .529 | 1.285[b] | 9.000 | 13.000 | .330 | .471 |
| | Hotelling's Trace | .890 | 1.285[b] | 9.000 | 13.000 | .330 | .471 |
| | Roy's Largest Root | .890 | 1.285[b] | 9.000 | 13.000 | .330 | .471 |

a. Design: Intercept + Group

Within Subjects Design: tau + SNR + tau * SNR

b. Exact statistic

## Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

| Within Subjects Effect | Mauchly's W | Approx. Chi-Square | df | Sig. | Epsilon[b] Greenhouse-Geisser | Huynh-Feldt | Lower-bound |
|---|---|---|---|---|---|---|---|
| tau | .667 | 7.984 | 5 | .158 | .823 | .986 | .333 |
| SNR | .532 | 12.432 | 5 | .030 | .708 | .827 | .333 |
| tau * SNR | .064 | 49.029 | 44 | .304 | .669 | 1.000 | .111 |

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + Group

Within Subjects Design: tau + SNR + tau * SNR

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

**Tests of Within-Subjects Effects**

Measure: MEASURE_1

| Source | | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|---|
| tau | Sphericity Assumed | 70824.945 | 3 | 23608.315 | 218.469 | .000 | .912 |
| | Greenhouse-Geisser | 70824.945 | 2.470 | 28675.354 | 218.469 | .000 | .912 |
| | Huynh-Feldt | 70824.945 | 2.958 | 23945.541 | 218.469 | .000 | .912 |
| | Lower-bound | 70824.945 | 1.000 | 70824.945 | 218.469 | .000 | .912 |
| tau * Group | Sphericity Assumed | 285.977 | 3 | 95.326 | .882 | .455 | .040 |
| | Greenhouse-Geisser | 285.977 | 2.470 | 115.785 | .882 | .439 | .040 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Huynh-Feldt | 285.977 | 2.958 | 96.687 | .882 | .454 | .040 |
| | Lower-bound | 285.977 | 1.000 | 285.977 | .882 | .358 | .040 |
| Error(tau) | Sphericity Assumed | 6807.927 | 63 | 108.062 | | | |
| | Greenhouse-Geisser | 6807.927 | 51.868 | 131.256 | | | |
| | Huynh-Feldt | 6807.927 | 62.113 | 109.606 | | | |
| | Lower-bound | 6807.927 | 21.000 | 324.187 | | | |
| SNR | Sphericity Assumed | 97578.944 | 3 | 32526.315 | 284.272 | .000 | .931 |
| | Greenhouse-Geisser | 97578.944 | 2.123 | 45967.778 | 284.272 | .000 | .931 |
| | Huynh-Feldt | 97578.944 | 2.480 | 39339.510 | 284.272 | .000 | .931 |
| | Lower-bound | 97578.944 | 1.000 | 97578.944 | 284.272 | .000 | .931 |
| SNR * Group | Sphericity Assumed | 906.000 | 3 | 302.000 | 2.639 | .057 | .112 |
| | Greenhouse-Geisser | 906.000 | 2.123 | 426.801 | 2.639 | .079 | .112 |
| | Huynh-Feldt | 906.000 | 2.480 | 365.259 | 2.639 | .069 | .112 |
| | Lower-bound | 906.000 | 1.000 | 906.000 | 2.639 | .119 | .112 |
| Error(SNR) | Sphericity Assumed | 7208.449 | 63 | 114.420 | | | |
| | Greenhouse-Geisser | 7208.449 | 44.578 | 161.704 | | | |
| | Huynh-Feldt | 7208.449 | 52.089 | 138.387 | | | |
| | Lower-bound | 7208.449 | 21.000 | 343.259 | | | |
| tau * SNR | Sphericity Assumed | 45630.560 | 9 | 5070.062 | 47.452 | .000 | .693 |
| | Greenhouse-Geisser | 45630.560 | 6.018 | 7582.016 | 47.452 | .000 | .693 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Huynh-Feldt | 45630.560 | 9.000 | 5070.062 | 47.452 | .000 | .693 |
| | Lower-bound | 45630.560 | 1.000 | 45630.560 | 47.452 | .000 | .693 |
| tau * SNR * Group | Sphericity Assumed | 1638.724 | 9 | 182.080 | 1.704 | .090 | .075 |
| | Greenhouse-Geisser | 1638.724 | 6.018 | 272.292 | 1.704 | .125 | .075 |
| | Huynh-Feldt | 1638.724 | 9.000 | 182.080 | 1.704 | .090 | .075 |
| | Lower-bound | 1638.724 | 1.000 | 1638.724 | 1.704 | .206 | .075 |
| Error(tau*SNR) | Sphericity Assumed | 20193.910 | 189 | 106.846 | | | |
| | Greenhouse-Geisser | 20193.910 | 126.384 | 159.783 | | | |
| | Huynh-Feldt | 20193.910 | 189.000 | 106.846 | | | |
| | Lower-bound | 20193.910 | 21.000 | 961.615 | | | |

**Tests of Within-Subjects Contrasts**

Measure: MEASURE_1

| Source | tau | SNR | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|---|---|
| tau | Linear | | 50586.364 | 1 | 50586.364 | 302.452 | .000 | .935 |
| | Quadratic | | 19870.668 | 1 | 19870.668 | 256.128 | .000 | .924 |
| | Cubic | | 367.913 | 1 | 367.913 | 4.637 | .043 | .181 |
| tau * Group | Linear | | 6.771 | 1 | 6.771 | .040 | .842 | .002 |
| | Quadratic | | 256.425 | 1 | 256.425 | 3.305 | .083 | .136 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Cubic | | 22.781 | 1 | 22.781 | .287 | .598 | .013 |
| Error(tau) | Linear | | 3512.343 | 21 | 167.254 | | | |
| | Quadratic | | 1629.203 | 21 | 77.581 | | | |
| | Cubic | | 1666.381 | 21 | 79.351 | | | |
| SNR | | Linear | 86628.521 | 1 | 86628.521 | 622.110 | .000 | .967 |
| | | Quadratic | 9252.189 | 1 | 9252.189 | 74.446 | .000 | .780 |
| | | Cubic | 1698.234 | 1 | 1698.234 | 21.300 | .000 | .504 |
| SNR * Group | | Linear | 797.365 | 1 | 797.365 | 5.726 | .026 | .214 |
| | | Quadratic | 1.363 | 1 | 1.363 | .011 | .918 | .001 |
| | | Cubic | 107.272 | 1 | 107.272 | 1.345 | .259 | .060 |
| Error(SNR) | | Linear | 2924.238 | 21 | 139.249 | | | |
| | | Quadratic | 2609.876 | 21 | 124.280 | | | |
| | | Cubic | 1674.334 | 21 | 79.730 | | | |
| tau * SNR | Linear | Linear | 40279.163 | 1 | 40279.163 | 390.409 | .000 | .949 |
| | | Quadratic | 2846.971 | 1 | 2846.971 | 19.892 | .000 | .486 |
| | | Cubic | 57.565 | 1 | 57.565 | .417 | .526 | .019 |
| | Quadratic | Linear | 1437.109 | 1 | 1437.109 | 17.022 | .000 | .448 |
| | | Quadratic | 17.367 | 1 | 17.367 | .201 | .659 | .009 |
| | | Cubic | 145.543 | 1 | 145.543 | 1.716 | .204 | .076 |
| | Cubic | Linear | 375.860 | 1 | 375.860 | 6.764 | .017 | .244 |
| | | Quadratic | 44.237 | 1 | 44.237 | .411 | .528 | .019 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Cubic | 426.745 | 1 | 426.745 | 2.696 | .116 | .114 |
| tau * SNR * Group | Linear | Linear | 79.670 | 1 | 79.670 | .772 | .389 | .035 |
| | | Quadratic | 70.050 | 1 | 70.050 | .489 | .492 | .023 |
| | | Cubic | 204.746 | 1 | 204.746 | 1.482 | .237 | .066 |
| | Quadratic | Linear | .105 | 1 | .105 | .001 | .972 | .000 |
| | | Quadratic | 3.330 | 1 | 3.330 | .038 | .846 | .002 |
| | | Cubic | 947.076 | 1 | 947.076 | 11.169 | .003 | .347 |
| | Cubic | Linear | 32.593 | 1 | 32.593 | .587 | .452 | .027 |
| | | Quadratic | 129.260 | 1 | 129.260 | 1.201 | .286 | .054 |
| | | Cubic | 171.895 | 1 | 171.895 | 1.086 | .309 | .049 |
| Error(tau*SNR) | Linear | Linear | 2166.607 | 21 | 103.172 | | | |
| | | Quadratic | 3005.587 | 21 | 143.123 | | | |
| | | Cubic | 2900.377 | 21 | 138.113 | | | |
| | Quadratic | Linear | 1772.996 | 21 | 84.428 | | | |
| | | Quadratic | 1816.237 | 21 | 86.487 | | | |
| | | Cubic | 1780.766 | 21 | 84.798 | | | |
| | Cubic | Linear | 1166.959 | 21 | 55.569 | | | |
| | | Quadratic | 2259.931 | 21 | 107.616 | | | |
| | | Cubic | 3324.450 | 21 | 158.307 | | | |

## Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Intercept | 3423030.116 | 1 | 3423030.116 | 7702.185 | .000 | .997 |
| Group | 6256.626 | 1 | 6256.626 | 14.078 | .001 | .401 |
| Error | 9332.888 | 21 | 444.423 | | | |

```
GLM tau1SNR3 tau1SNR0 tau1SNRm3 tau1SNRm6 tau2SNR3 tau2SNR0 tau2SNRm3 tau2SNRm6 tau3SNR3 tau3SNR0
    tau3SNRm3 tau3SNRm6 notauSNR3 notauSNR0 notauSNRm3 notauSNRm6
  /WSFACTOR=tau 4 Simple SNR 4 Polynomial
  /METHOD=SSTYPE(3)
  /CRITERIA=ALPHA(.05)
  /WSDESIGN=tau SNR tau*SNR
  /EMMEANS=TABLES(tau*SNR) COMPARE(tau) ADJ(BONFERRONI).
```

## General Linear Model

**Notes**

| | | |
|---|---|---|
| Output Created | | 07-JUL-2018 14:12:03 |
| Comments | | |
| Input | Data | \\myfiles.uwo.pri\vparsa\Documents\sAPDnNHChildrenRAUs.sav |
| | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 23 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing. |
| | Cases Used | Statistics are based on all cases with valid data for all variables in the model. |

| | | |
|---|---|---|
| Syntax | | GLM tau1SNR3 tau1SNR0 tau1SNRm3 tau1SNRm6 tau2SNR3 tau2SNR0 tau2SNRm3 tau2SNRm6 tau3SNR3 tau3SNR0<br>tau3SNRm3 tau3SNRm6 notauSNR3 notauSNR0 notauSNRm3 notauSNRm6<br>/WSFACTOR=tau 4 Simple SNR 4 Polynomial<br>/METHOD=SSTYPE(3)<br>/CRITERIA=ALPHA(.05)<br>/WSDESIGN=tau SNR tau*SNR<br>/EMMEANS=TABLES(tau*SNR) COMPARE(tau) ADJ(BONFERRONI). |
| Resources | Processor Time | 00:00:00.02 |
| | Elapsed Time | 00:00:00.02 |

### Within-Subjects Factors

Measure: MEASURE_1

| tau | SNR | Dependent Variable |
|---|---|---|
| 1 | 1 | tau1SNR3 |
| | 2 | tau1SNR0 |
| | 3 | tau1SNRm3 |
| | 4 | tau1SNRm6 |
| 2 | 1 | tau2SNR3 |
| | 2 | tau2SNR0 |
| | 3 | tau2SNRm3 |
| | 4 | tau2SNRm6 |
| 3 | 1 | tau3SNR3 |
| | 2 | tau3SNR0 |
| | 3 | tau3SNRm3 |
| | 4 | tau3SNRm6 |
| 4 | 1 | notauSNR3 |
| | 2 | notauSNR0 |
| | 3 | notauSNRm3 |
| | 4 | notauSNRm6 |

**Multivariate Tests[a]**

| Effect | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| tau | Pillai's Trace | .962 | 169.328[b] | 3.000 | 20.000 | .000 |
| | Wilks' Lambda | .038 | 169.328[b] | 3.000 | 20.000 | .000 |
| | Hotelling's Trace | 25.399 | 169.328[b] | 3.000 | 20.000 | .000 |
| | Roy's Largest Root | 25.399 | 169.328[b] | 3.000 | 20.000 | .000 |
| SNR | Pillai's Trace | .967 | 196.333[b] | 3.000 | 20.000 | .000 |
| | Wilks' Lambda | .033 | 196.333[b] | 3.000 | 20.000 | .000 |
| | Hotelling's Trace | 29.450 | 196.333[b] | 3.000 | 20.000 | .000 |
| | Roy's Largest Root | 29.450 | 196.333[b] | 3.000 | 20.000 | .000 |
| tau * SNR | Pillai's Trace | .961 | 37.934[b] | 9.000 | 14.000 | .000 |
| | Wilks' Lambda | .039 | 37.934[b] | 9.000 | 14.000 | .000 |
| | Hotelling's Trace | 24.386 | 37.934[b] | 9.000 | 14.000 | .000 |
| | Roy's Largest Root | 24.386 | 37.934[b] | 9.000 | 14.000 | .000 |

a. Design: Intercept

Within Subjects Design: tau + SNR + tau * SNR

b. Exact statistic

## Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

| Within Subjects Effect | Mauchly's W | Approx. Chi-Square | df | Sig. | Epsilon[b] Greenhouse-Geisser | Huynh-Feldt | Lower-bound |
|---|---|---|---|---|---|---|---|
| tau | .743 | 6.145 | 5 | .293 | .857 | .980 | .333 |
| SNR | .543 | 12.656 | 5 | .027 | .711 | .790 | .333 |
| tau * SNR | .060 | 53.018 | 44 | .183 | .669 | .949 | .111 |

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept

Within Subjects Design: tau + SNR + tau * SNR

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

## Tests of Within-Subjects Effects

Measure: MEASURE_1

| Source | | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| tau | Sphericity Assumed | 70821.931 | 3 | 23607.310 | 219.637 | .000 |
| | Greenhouse-Geisser | 70821.931 | 2.570 | 27560.801 | 219.637 | .000 |
| | Huynh-Feldt | 70821.931 | 2.939 | 24098.786 | 219.637 | .000 |
| | Lower-bound | 70821.931 | 1.000 | 70821.931 | 219.637 | .000 |
| Error(tau) | Sphericity Assumed | 7093.904 | 66 | 107.483 | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Greenhouse-Geisser | 7093.904 | 56.533 | 125.484 | | |
| | Huynh-Feldt | 7093.904 | 64.654 | 109.721 | | |
| | Lower-bound | 7093.904 | 22.000 | 322.450 | | |
| SNR | Sphericity Assumed | 97068.795 | 3 | 32356.265 | 263.174 | .000 |
| | Greenhouse-Geisser | 97068.795 | 2.134 | 45483.960 | 263.174 | .000 |
| | Huynh-Feldt | 97068.795 | 2.370 | 40954.740 | 263.174 | .000 |
| | Lower-bound | 97068.795 | 1.000 | 97068.795 | 263.174 | .000 |
| Error(SNR) | Sphericity Assumed | 8114.449 | 66 | 122.946 | | |
| | Greenhouse-Geisser | 8114.449 | 46.951 | 172.828 | | |
| | Huynh-Feldt | 8114.449 | 52.143 | 155.618 | | |
| | Lower-bound | 8114.449 | 22.000 | 368.839 | | |
| tau * SNR | Sphericity Assumed | 45965.962 | 9 | 5107.329 | 46.318 | .000 |
| | Greenhouse-Geisser | 45965.962 | 6.019 | 7636.413 | 46.318 | .000 |
| | Huynh-Feldt | 45965.962 | 8.538 | 5383.649 | 46.318 | .000 |
| | Lower-bound | 45965.962 | 1.000 | 45965.962 | 46.318 | .000 |
| Error(tau*SNR) | Sphericity Assumed | 21832.634 | 198 | 110.266 | | |
| | Greenhouse-Geisser | 21832.634 | 132.425 | 164.868 | | |
| | Huynh-Feldt | 21832.634 | 187.838 | 116.231 | | |
| | Lower-bound | 21832.634 | 22.000 | 992.392 | | |

## Tests of Within-Subjects Contrasts

Measure: MEASURE_1

| Source | tau | SNR | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| tau | Level 1 vs. Level 4 | | 86149.566 | 1 | 86149.566 | 280.334 | .000 |
| | Level 2 vs. Level 4 | | 122878.255 | 1 | 122878.255 | 491.133 | .000 |
| | Level 3 vs. Level 4 | | 50074.042 | 1 | 50074.042 | 384.304 | .000 |
| Error(tau) | Level 1 vs. Level 4 | | 6760.842 | 22 | 307.311 | | |
| | Level 2 vs. Level 4 | | 5504.254 | 22 | 250.193 | | |
| | Level 3 vs. Level 4 | | 2866.553 | 22 | 130.298 | | |
| SNR | | Linear | 21517.507 | 1 | 21517.507 | 508.797 | .000 |
| | | Quadratic | 2314.982 | 1 | 2314.982 | 78.016 | .000 |
| | | Cubic | 434.710 | 1 | 434.710 | 21.472 | .000 |
| Error(SNR) | | Linear | 930.401 | 22 | 42.291 | | |
| | | Quadratic | 652.810 | 22 | 29.673 | | |
| | | Cubic | 445.402 | 22 | 20.246 | | |
| tau * SNR | Level 1 vs. Level 4 | Linear | 77621.394 | 1 | 77621.394 | 363.698 | .000 |
| | | Quadratic | 5609.769 | 1 | 5609.769 | 17.999 | .000 |
| | | Cubic | 421.347 | 1 | 421.347 | 1.385 | .252 |
| | Level 2 vs. Level 4 | Linear | 43855.846 | 1 | 43855.846 | 245.944 | .000 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Quadratic | 2459.128 | 1 | 2459.128 | 14.228 | .001 |
| | | Cubic | 126.834 | 1 | 126.834 | .474 | .498 |
| | Level 3 vs. Level 4 | Linear | 21055.964 | 1 | 21055.964 | 191.335 | .000 |
| | | Quadratic | 1143.128 | 1 | 1143.128 | 4.720 | .041 |
| | | Cubic | 1302.804 | 1 | 1302.804 | 3.563 | .072 |
| Error(tau*SNR) | Level 1 vs. Level 4 | Linear | 4695.299 | 22 | 213.423 | | |
| | | Quadratic | 6856.677 | 22 | 311.667 | | |
| | | Cubic | 6690.925 | 22 | 304.133 | | |
| | Level 2 vs. Level 4 | Linear | 3922.954 | 22 | 178.316 | | |
| | | Quadratic | 3802.332 | 22 | 172.833 | | |
| | | Cubic | 5881.326 | 22 | 267.333 | | |
| | Level 3 vs. Level 4 | Linear | 2421.045 | 22 | 110.048 | | |
| | | Quadratic | 5328.578 | 22 | 242.208 | | |
| | | Cubic | 8043.579 | 22 | 365.617 | | |

## Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Intercept | 860568.665 | 1 | 860568.665 | 4857.755 | .000 |

| | | | | | |
|---|---|---|---|---|---|
| Error | 3897.379 | 22 | 177.154 | | |

## Estimated Marginal Means

## tau * SNR

### Estimates

Measure: MEASURE_1

| tau | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| 1 | 1 | 107.858 | 1.773 | 104.181 | 111.535 |
| | 2 | 104.841 | 3.041 | 98.534 | 111.149 |
| | 3 | 107.221 | 2.839 | 101.333 | 113.109 |
| | 4 | 98.870 | 2.833 | 92.994 | 104.746 |
| 2 | 1 | 121.275 | 1.194 | 118.799 | 123.751 |
| | 2 | 115.356 | 1.901 | 111.413 | 119.299 |
| | 3 | 113.875 | 2.056 | 109.610 | 118.140 |
| | 4 | 92.067 | 3.197 | 85.438 | 98.697 |
| 3 | 1 | 114.251 | 1.542 | 111.052 | 117.450 |
| | 2 | 110.256 | 2.590 | 104.885 | 115.627 |
| | 3 | 95.832 | 2.443 | 90.765 | 100.899 |
| | 4 | 69.368 | 2.370 | 64.453 | 74.283 |
| 4 | 1 | 109.376 | 2.476 | 104.241 | 114.512 |

| | | | | | |
|---|---|---|---|---|---|
| | 2 | 92.168 | 2.729 | 86.508 | 97.829 |
| | 3 | 74.310 | 2.913 | 68.269 | 80.351 |
| | 4 | 20.533 | 3.648 | 12.969 | 28.098 |

**Pairwise Comparisons**

Measure: MEASURE_1

| SNR | (I) tau | (J) tau | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| 1 | 1 | 2 | -13.417* | 1.908 | .000 | -18.946 | -7.888 |
| | | 3 | -6.393* | 2.147 | .042 | -12.615 | -.170 |
| | | 4 | -1.518 | 2.514 | 1.000 | -8.806 | 5.770 |
| | 2 | 1 | 13.417* | 1.908 | .000 | 7.888 | 18.946 |
| | | 3 | 7.024* | 1.763 | .004 | 1.914 | 12.134 |
| | | 4 | 11.899* | 2.600 | .001 | 4.362 | 19.435 |
| | 3 | 1 | 6.393* | 2.147 | .042 | .170 | 12.615 |
| | | 2 | -7.024* | 1.763 | .004 | -12.134 | -1.914 |
| | | 4 | 4.875 | 2.603 | .447 | -2.671 | 12.421 |
| | 4 | 1 | 1.518 | 2.514 | 1.000 | -5.770 | 8.806 |
| | | 2 | -11.899* | 2.600 | .001 | -19.435 | -4.362 |
| | | 3 | -4.875 | 2.603 | .447 | -12.421 | 2.671 |
| 2 | 1 | 2 | -10.514* | 3.469 | .037 | -20.568 | -.460 |
| | | 3 | -5.415 | 2.992 | .504 | -14.086 | 3.257 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 4 | 12.673* | 3.294 | .005 | 3.125 | 22.221 |
| | 2 | 1 | 10.514* | 3.469 | .037 | .460 | 20.568 |
| | | 3 | 5.099 | 3.381 | .874 | -4.700 | 14.898 |
| | | 4 | 23.187* | 2.565 | .000 | 15.752 | 30.623 |
| | 3 | 1 | 5.415 | 2.992 | .504 | -3.257 | 14.086 |
| | | 2 | -5.099 | 3.381 | .874 | -14.898 | 4.700 |
| | | 4 | 18.088* | 2.986 | .000 | 9.434 | 26.742 |
| | 4 | 1 | -12.673* | 3.294 | .005 | -22.221 | -3.125 |
| | | 2 | -23.187* | 2.565 | .000 | -30.623 | -15.752 |
| | | 3 | -18.088* | 2.986 | .000 | -26.742 | -9.434 |
| 3 | 1 | 2 | -6.654 | 2.580 | .103 | -14.131 | .823 |
| | | 3 | 11.389* | 3.631 | .029 | .864 | 21.915 |
| | | 4 | 32.911* | 2.949 | .000 | 24.364 | 41.458 |
| | 2 | 1 | 6.654 | 2.580 | .103 | -.823 | 14.131 |
| | | 3 | 18.043* | 2.919 | .000 | 9.583 | 26.503 |
| | | 4 | 39.565* | 3.198 | .000 | 30.297 | 48.834 |
| | 3 | 1 | -11.389* | 3.631 | .029 | -21.915 | -.864 |
| | | 2 | -18.043* | 2.919 | .000 | -26.503 | -9.583 |
| | | 4 | 21.522* | 3.309 | .000 | 11.931 | 31.113 |
| | 4 | 1 | -32.911* | 2.949 | .000 | -41.458 | -24.364 |
| | | 2 | -39.565* | 3.198 | .000 | -48.834 | -30.297 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 3 | -21.522* | 3.309 | .000 | -31.113 | -11.931 |
| 4 | 1 | 2 | 6.803 | 3.876 | .559 | -4.431 | 18.037 |
| | | 3 | 29.502* | 2.834 | .000 | 21.288 | 37.717 |
| | | 4 | 78.337* | 4.852 | .000 | 64.272 | 92.402 |
| | 2 | 1 | -6.803 | 3.876 | .559 | -18.037 | 4.431 |
| | | 3 | 22.699* | 3.071 | .000 | 13.799 | 31.600 |
| | | 4 | 71.534* | 3.769 | .000 | 60.611 | 82.457 |
| | 3 | 1 | -29.502* | 2.834 | .000 | -37.717 | -21.288 |
| | | 2 | -22.699* | 3.071 | .000 | -31.600 | -13.799 |
| | | 4 | 48.835* | 3.199 | .000 | 39.561 | 58.108 |
| | 4 | 1 | -78.337* | 4.852 | .000 | -92.402 | -64.272 |
| | | 2 | -71.534* | 3.769 | .000 | -82.457 | -60.611 |
| | | 3 | -48.835* | 3.199 | .000 | -58.108 | -39.561 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

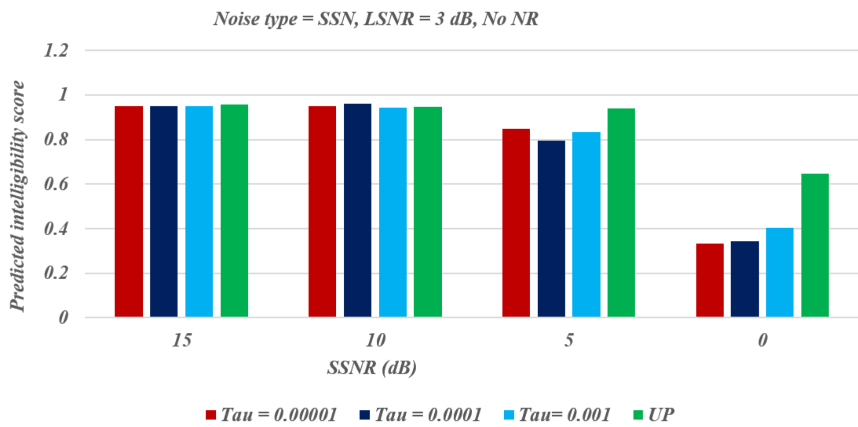
| SNR | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| 1 | Pillai's trace | .714 | 16.659[a] | 3.000 | 20.000 | .000 |

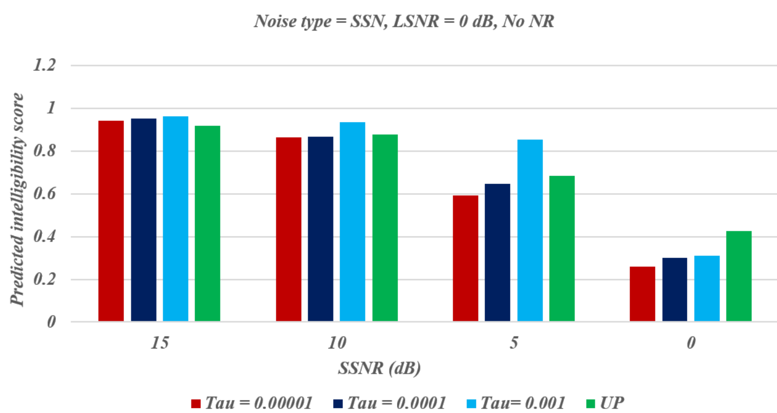
| | | | | | | |
|---|---|---|---|---|---|---|
| | Wilks' lambda | .286 | 16.659[a] | 3.000 | 20.000 | .000 |
| | Hotelling's trace | 2.499 | 16.659[a] | 3.000 | 20.000 | .000 |
| | Roy's largest root | 2.499 | 16.659[a] | 3.000 | 20.000 | .000 |
| 2 | Pillai's trace | .816 | 29.467[a] | 3.000 | 20.000 | .000 |
| | Wilks' lambda | .184 | 29.467[a] | 3.000 | 20.000 | .000 |
| | Hotelling's trace | 4.420 | 29.467[a] | 3.000 | 20.000 | .000 |
| | Roy's largest root | 4.420 | 29.467[a] | 3.000 | 20.000 | .000 |
| 3 | Pillai's trace | .886 | 51.643[a] | 3.000 | 20.000 | .000 |
| | Wilks' lambda | .114 | 51.643[a] | 3.000 | 20.000 | .000 |
| | Hotelling's trace | 7.747 | 51.643[a] | 3.000 | 20.000 | .000 |
| | Roy's largest root | 7.747 | 51.643[a] | 3.000 | 20.000 | .000 |
| 4 | Pillai's trace | .947 | 118.621[a] | 3.000 | 20.000 | .000 |
| | Wilks' lambda | .053 | 118.621[a] | 3.000 | 20.000 | .000 |
| | Hotelling's trace | 17.793 | 118.621[a] | 3.000 | 20.000 | .000 |
| | Roy's largest root | 17.793 | 118.621[a] | 3.000 | 20.000 | .000 |

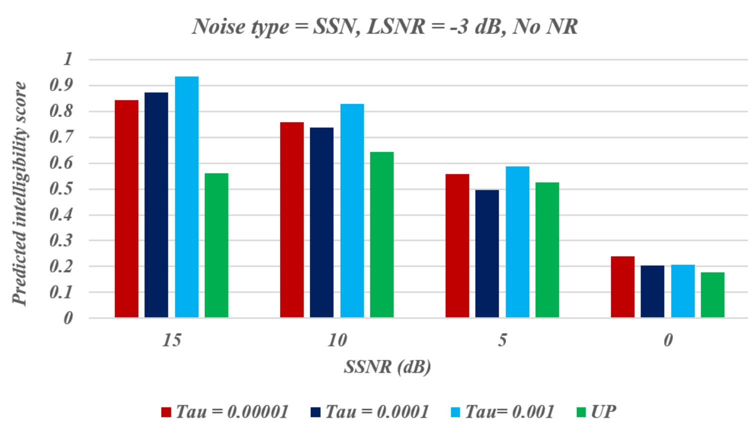
Each F tests the multivariate simple effects of tau within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

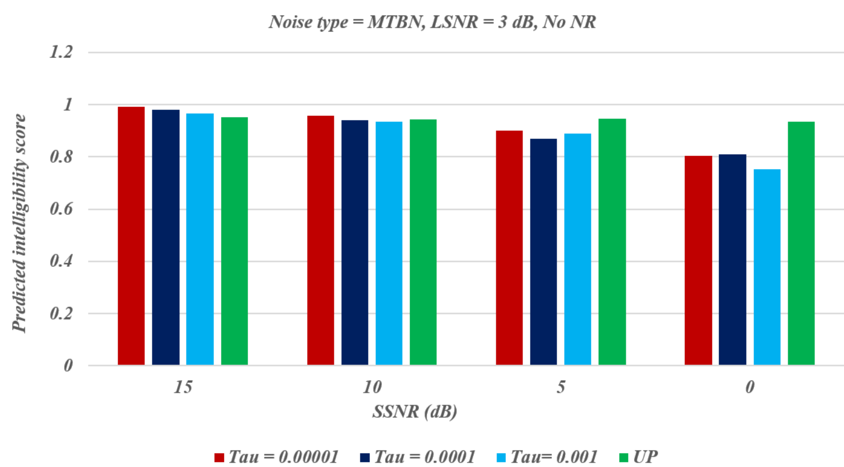
a. Exact statistic

# Appendix B: Comprehensive Objective Assessment of Dynamic EE Results

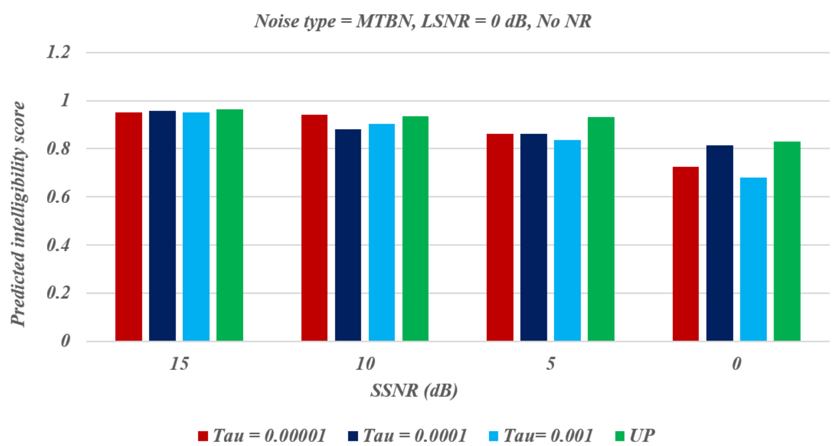


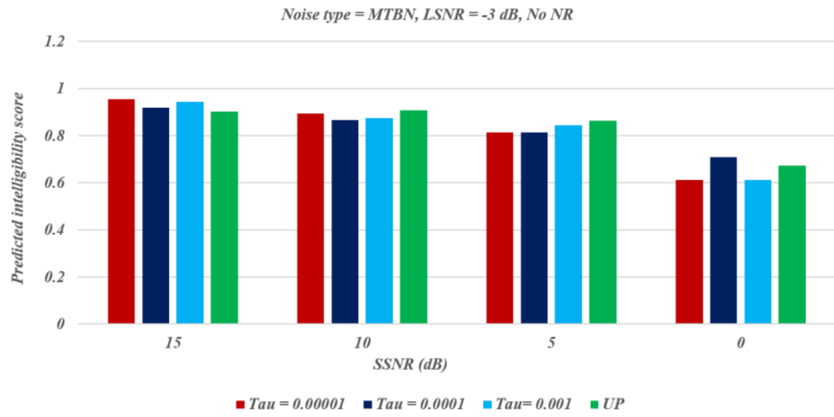





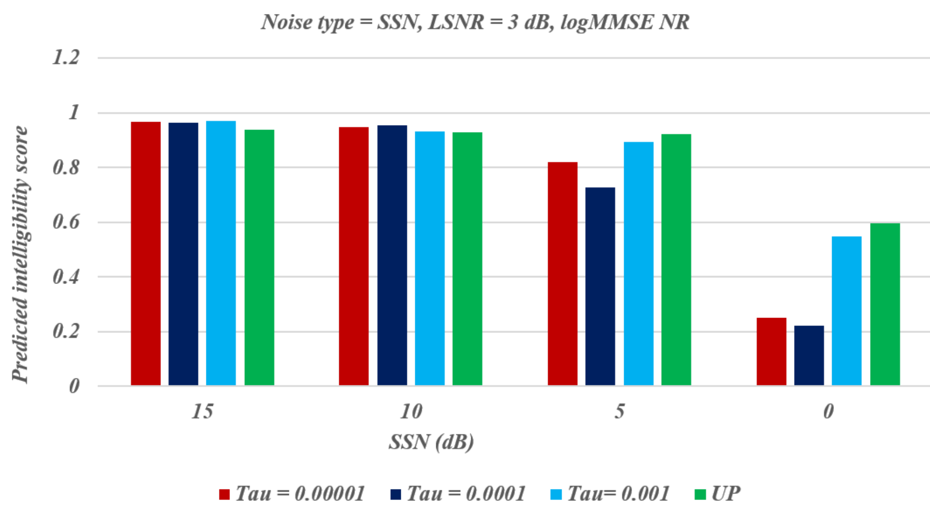
Noise type = MTBN, LSNR = 3 dB, No NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

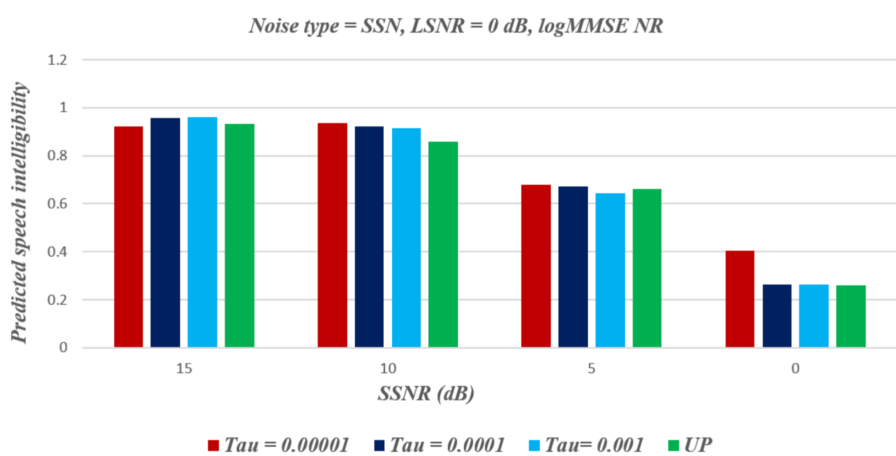
Noise type = MTBN, LSNR = 0 dB, No NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP



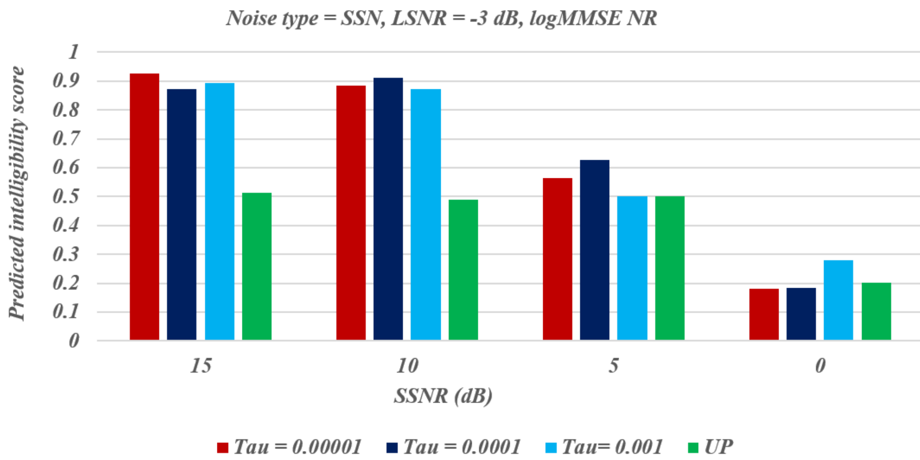
Noise type = MTBN, LSNR = -3 dB, No NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

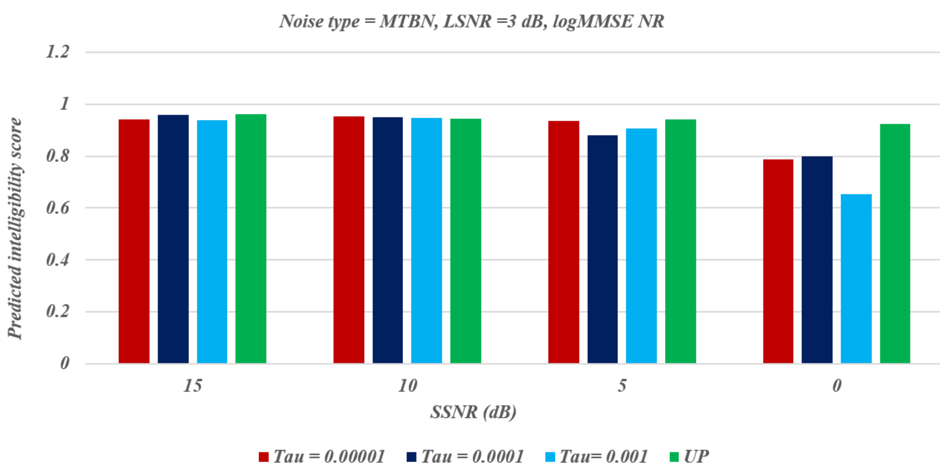



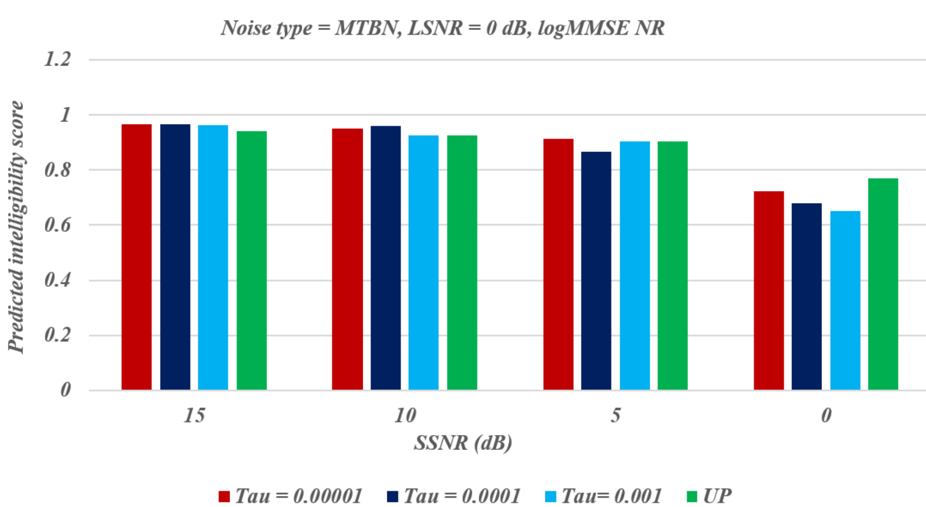
Noise type = SSN, LSNR = 3 dB, logMMSE NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSN (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

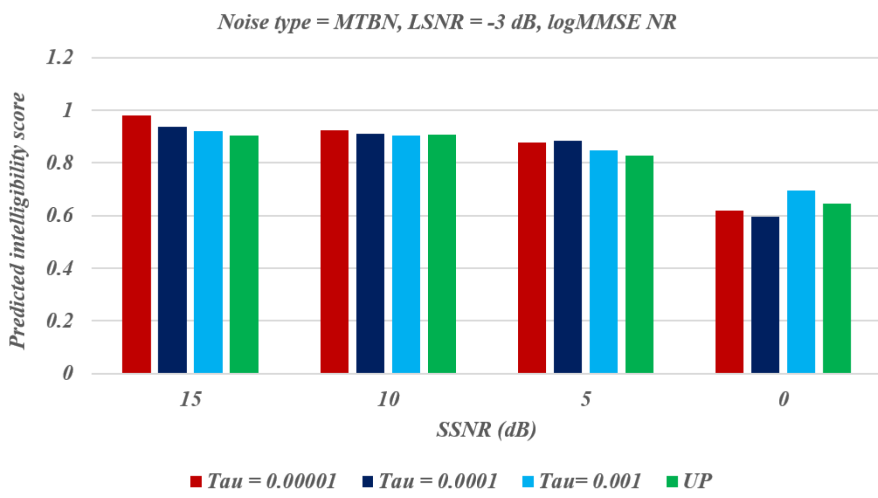



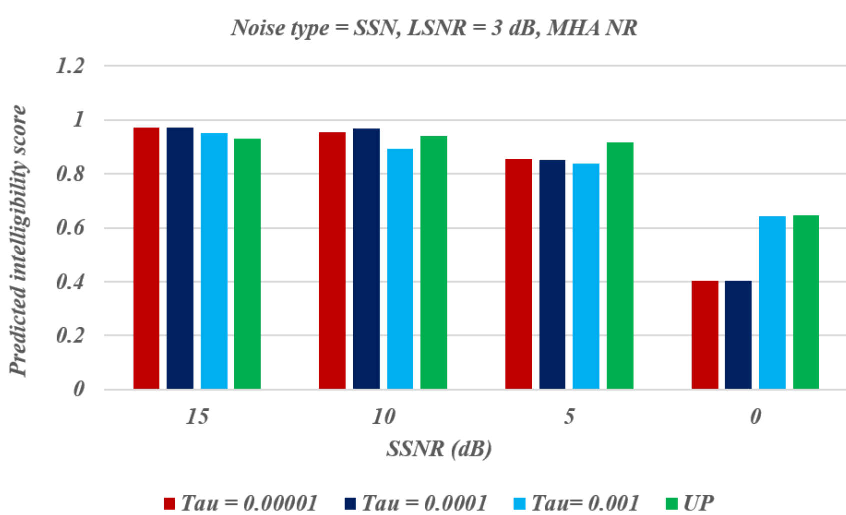
Noise type = SSN, LSNR = 0 dB, logMMSE NR
Predicted speech intelligibility
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

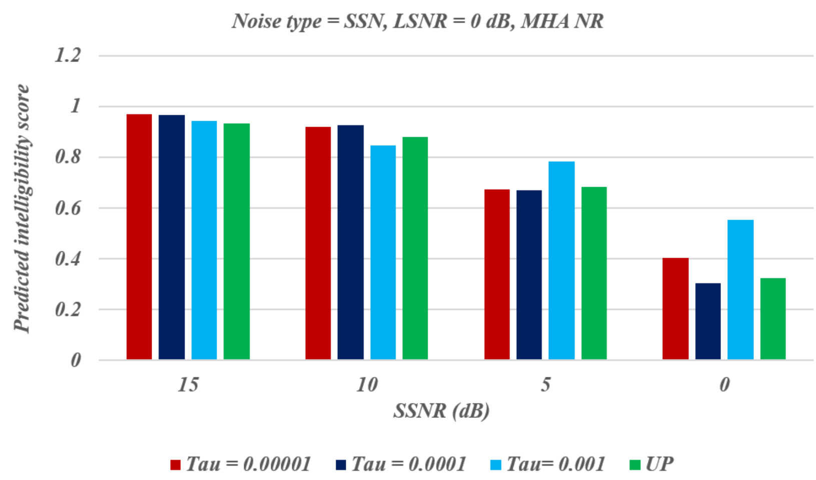

Noise type = SSN, LSNR = -3 dB, logMMSE NR
Predicted intelligibility score
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

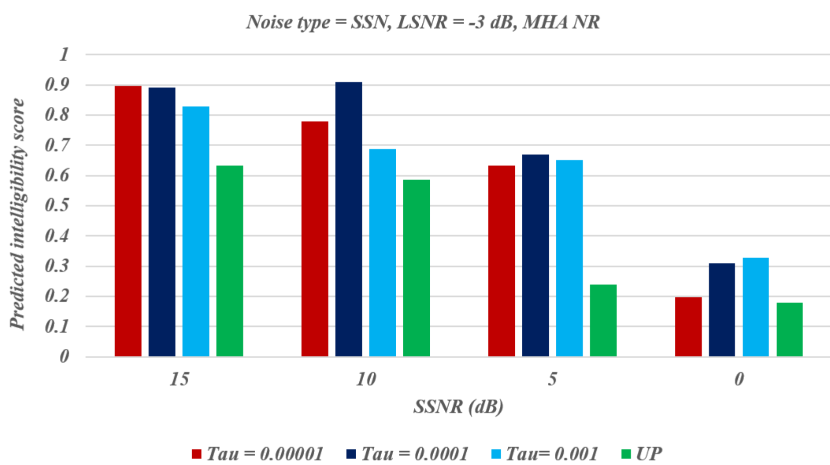

Noise type = MTBN, LSNR =3 dB, logMMSE NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

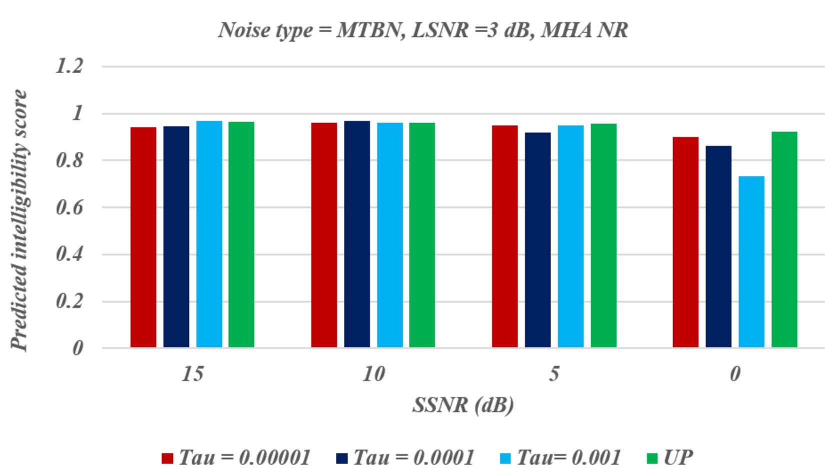

Noise type = MTBN, LSNR = 0 dB, logMMSE NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

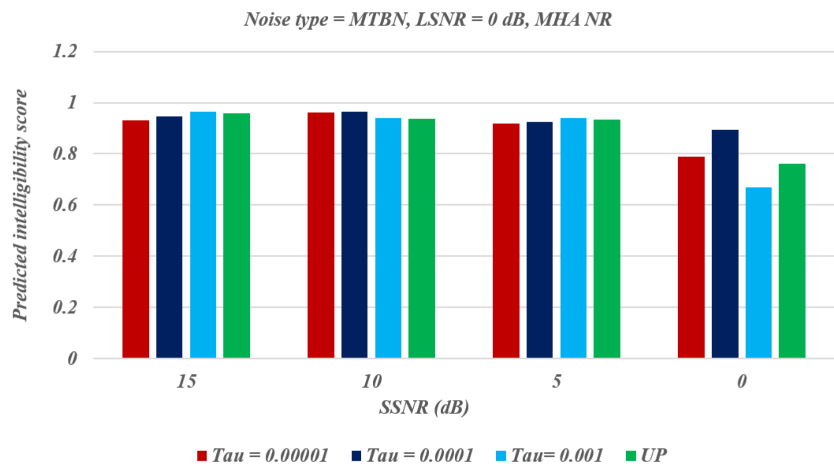

Noise type = MTBN, LSNR = -3 dB, logMMSE NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

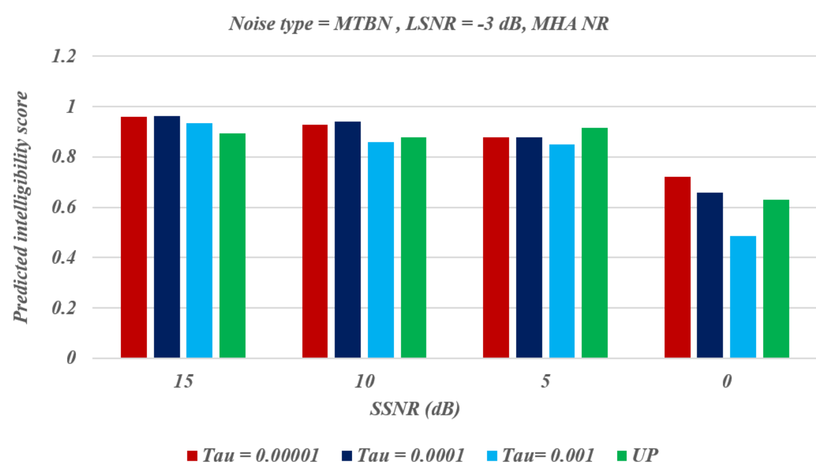

Noise type = SSN, LSNR = 3 dB, MHA NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP


Noise type = SSN, LSNR = 0 dB, MHA NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP


Noise type = SSN, LSNR = -3 dB, MHA NR
Predicted intelligibility score
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP


Noise type = MTBN, LSNR =3 dB, MHA NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP


Noise type = MTBN, LSNR = 0 dB, MHA NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP


Noise type = MTBN , LSNR = -3 dB, MHA NR
Predicted intelligibility score
1.2
1
0.8
0.6
0.4
0.2
0
15
10
5
0
SSNR (dB)
Tau = 0.00001
Tau = 0.0001
Tau= 0.001
UP

# Appendix C: Static EE Speech Intelligibility Statistical Report

## Stationary Background Noise Experiment

### General Linear Model

**Notes**

| | | |
|---|---|---|
| Output Created | | 13-DEC-2018 08:32:53 |
| Comments | | |
| Input | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 20 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing. |
| | Cases Used | Statistics are based on all cases with valid data for all variables in the model. |

| | |
|---|---|
| Syntax | GLM UP_4 UP_0 UP_3 UP_6 SEE_4 SEE_0 SEE_3 SEE_6 MMSESEE_4 MMSESEE_0 MMSESEE_3 MMSESEE_6 MHASEE_4<br>MHASEE_0 MHASEE_3 MHASEE_6 BY Group<br>/WSFACTOR=processing 4 Polynomial SNR 4 Polynomial<br>/METHOD=SSTYPE(3)<br>/EMMEANS=TABLES(Group) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(processing) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(Group*processing)<br>/EMMEANS=TABLES(Group*SNR)<br>/EMMEANS=TABLES(processing*SNR)<br>/EMMEANS=TABLES(Group*processing*SNR)<br>/EMMEANS=TABLES(processing*SNR) COMPARE(processing)ADJ(BONFERRONI)<br>/EMMEANS=TABLES(Group*processing*SNR) COMPARE(processing)ADJ(BONFERRONI)<br>/CRITERIA=ALPHA(.05)<br>/WSDESIGN=processing SNR processing*SNR<br>/DESIGN=Group. |

| | | |
|---|---|---|
| Resources | Processor Time | 00:00:00.08 |
| | Elapsed Time | 00:00:00.12 |

[DataSet1]

**Within-Subjects Factors**

Measure: MEASURE_1

| processing | SNR | Dependent Variable |
|---|---|---|
| 1 | 1 | UP_4 |
| | 2 | UP_0 |
| | 3 | UP_3 |
| | 4 | UP_6 |
| 2 | 1 | SEE_4 |
| | 2 | SEE_0 |
| | 3 | SEE_3 |
| | 4 | SEE_6 |
| 3 | 1 | MMSESEE_4 |
| | 2 | MMSESEE_0 |
| | 3 | MMSESEE_3 |
| | 4 | MMSESEE_6 |
| 4 | 1 | MHASEE_4 |
| | 2 | MHASEE_0 |

| | |
|---|---|
| 3 | MHASEE_3 |
| 4 | MHASEE_6 |

**Between-Subjects Factors**

| | | N |
|---|---|---|
| Group | APD | 10 |
| | NC | 10 |

**Multivariate Tests[a]**

| Effect | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| processing | Pillai's Trace | .816 | 23.705[b] | 3.000 | 16.000 | .000 |
| | Wilks' Lambda | .184 | 23.705[b] | 3.000 | 16.000 | .000 |
| | Hotelling's Trace | 4.445 | 23.705[b] | 3.000 | 16.000 | .000 |
| | Roy's Largest Root | 4.445 | 23.705[b] | 3.000 | 16.000 | .000 |
| processing * Group | Pillai's Trace | .409 | 3.698[b] | 3.000 | 16.000 | .034 |
| | Wilks' Lambda | .591 | 3.698[b] | 3.000 | 16.000 | .034 |
| | Hotelling's Trace | .693 | 3.698[b] | 3.000 | 16.000 | .034 |
| | Roy's Largest Root | .693 | 3.698[b] | 3.000 | 16.000 | .034 |
| SNR | Pillai's Trace | .980 | 255.612[b] | 3.000 | 16.000 | .000 |
| | Wilks' Lambda | .020 | 255.612[b] | 3.000 | 16.000 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Hotelling's Trace | 47.927 | 255.612[b] | 3.000 | 16.000 | .000 |
| | Roy's Largest Root | 47.927 | 255.612[b] | 3.000 | 16.000 | .000 |
| SNR * Group | Pillai's Trace | .060 | .339[b] | 3.000 | 16.000 | .797 |
| | Wilks' Lambda | .940 | .339[b] | 3.000 | 16.000 | .797 |
| | Hotelling's Trace | .064 | .339[b] | 3.000 | 16.000 | .797 |
| | Roy's Largest Root | .064 | .339[b] | 3.000 | 16.000 | .797 |
| processing * SNR | Pillai's Trace | .917 | 12.280[b] | 9.000 | 10.000 | .000 |
| | Wilks' Lambda | .083 | 12.280[b] | 9.000 | 10.000 | .000 |
| | Hotelling's Trace | 11.052 | 12.280[b] | 9.000 | 10.000 | .000 |
| | Roy's Largest Root | 11.052 | 12.280[b] | 9.000 | 10.000 | .000 |
| processing * SNR * Group | Pillai's Trace | .409 | .768[b] | 9.000 | 10.000 | .649 |
| | Wilks' Lambda | .591 | .768[b] | 9.000 | 10.000 | .649 |
| | Hotelling's Trace | .691 | .768[b] | 9.000 | 10.000 | .649 |
| | Roy's Largest Root | .691 | .768[b] | 9.000 | 10.000 | .649 |

a. Design: Intercept + Group

Within Subjects Design: processing + SNR + processing * SNR

b. Exact statistic

**Mauchly's Test of Sphericity[a]**

Measure: MEASURE_1

| Within Subjects Effect | Mauchly's W | Approx. Chi-Square | df | Sig. | Epsilon[b] | | |
|---|---|---|---|---|---|---|---|
| | | | | | Greenhouse-Geisser | Huynh-Feldt | Lower-bound |
| processing | .727 | 5.340 | 5 | .376 | .813 | 1.000 | .333 |
| SNR | .570 | 9.413 | 5 | .094 | .785 | .960 | .333 |
| processing * SNR | .031 | 51.607 | 44 | .233 | .663 | 1.000 | .111 |

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + Group

Within Subjects Design: processing + SNR + processing * SNR

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

**Tests of Within-Subjects Effects**

Measure: MEASURE_1

| Source | | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| processing | Sphericity Assumed | 14965.884 | 3 | 4988.628 | 30.322 | .000 |
| | Greenhouse-Geisser | 14965.884 | 2.440 | 6134.132 | 30.322 | .000 |
| | Huynh-Feldt | 14965.884 | 3.000 | 4988.628 | 30.322 | .000 |
| | Lower-bound | 14965.884 | 1.000 | 14965.884 | 30.322 | .000 |
| processing * Group | Sphericity Assumed | 2601.386 | 3 | 867.129 | 5.271 | .003 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Greenhouse-Geisser | 2601.386 | 2.440 | 1066.242 | 5.271 | .006 |
| | Huynh-Feldt | 2601.386 | 3.000 | 867.129 | 5.271 | .003 |
| | Lower-bound | 2601.386 | 1.000 | 2601.386 | 5.271 | .034 |
| Error(processing) | Sphericity Assumed | 8884.202 | 54 | 164.522 | | |
| | Greenhouse-Geisser | 8884.202 | 43.916 | 202.300 | | |
| | Huynh-Feldt | 8884.202 | 54.000 | 164.522 | | |
| | Lower-bound | 8884.202 | 18.000 | 493.567 | | |
| SNR | Sphericity Assumed | 244564.546 | 3 | 81521.515 | 422.722 | .000 |
| | Greenhouse-Geisser | 244564.546 | 2.354 | 103895.699 | 422.722 | .000 |
| | Huynh-Feldt | 244564.546 | 2.881 | 84883.933 | 422.722 | .000 |
| | Lower-bound | 244564.546 | 1.000 | 244564.546 | 422.722 | .000 |
| SNR * Group | Sphericity Assumed | 140.986 | 3 | 46.995 | .244 | .865 |
| | Greenhouse-Geisser | 140.986 | 2.354 | 59.894 | .244 | .819 |
| | Huynh-Feldt | 140.986 | 2.881 | 48.934 | .244 | .858 |
| | Lower-bound | 140.986 | 1.000 | 140.986 | .244 | .628 |
| Error(SNR) | Sphericity Assumed | 10413.838 | 54 | 192.849 | | |
| | Greenhouse-Geisser | 10413.838 | 42.371 | 245.778 | | |
| | Huynh-Feldt | 10413.838 | 51.861 | 200.803 | | |
| | Lower-bound | 10413.838 | 18.000 | 578.547 | | |
| processing * SNR | Sphericity Assumed | 13605.777 | 9 | 1511.753 | 12.928 | .000 |
| | Greenhouse-Geisser | 13605.777 | 5.963 | 2281.844 | 12.928 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Huynh-Feldt | 13605.777 | 9.000 | 1511.753 | 12.928 | .000 |
| | Lower-bound | 13605.777 | 1.000 | 13605.777 | 12.928 | .002 |
| processing * SNR * Group | Sphericity Assumed | 564.764 | 9 | 62.752 | .537 | .846 |
| | Greenhouse-Geisser | 564.764 | 5.963 | 94.717 | .537 | .778 |
| | Huynh-Feldt | 564.764 | 9.000 | 62.752 | .537 | .846 |
| | Lower-bound | 564.764 | 1.000 | 564.764 | .537 | .473 |
| Error(processing*SNR) | Sphericity Assumed | 18943.673 | 162 | 116.936 | | |
| | Greenhouse-Geisser | 18943.673 | 107.327 | 176.504 | | |
| | Huynh-Feldt | 18943.673 | 162.000 | 116.936 | | |
| | Lower-bound | 18943.673 | 18.000 | 1052.426 | | |

**Tests of Within-Subjects Contrasts**

Measure: MEASURE_1

| Source | processing | SNR | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| processing | Linear | | 1128.632 | 1 | 1128.632 | 6.514 | .020 |
| | Quadratic | | 10837.334 | 1 | 10837.334 | 48.622 | .000 |
| | Cubic | | 2999.917 | 1 | 2999.917 | 30.794 | .000 |
| processing * Group | Linear | | 2012.661 | 1 | 2012.661 | 11.617 | .003 |
| | Quadratic | | 468.704 | 1 | 468.704 | 2.103 | .164 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Cubic | | 120.022 | 1 | 120.022 | 1.232 | .282 |
| Error(processing) | Linear | | 3118.641 | 18 | 173.258 | | |
| | Quadratic | | 4012.020 | 18 | 222.890 | | |
| | Cubic | | 1753.541 | 18 | 97.419 | | |
| SNR | | Linear | 238386.173 | 1 | 238386.173 | 844.891 | .000 |
| | | Quadratic | 5486.380 | 1 | 5486.380 | 55.696 | .000 |
| | | Cubic | 691.993 | 1 | 691.993 | 3.497 | .078 |
| SNR * Group | | Linear | .889 | 1 | .889 | .003 | .956 |
| | | Quadratic | 89.790 | 1 | 89.790 | .912 | .352 |
| | | Cubic | 50.307 | 1 | 50.307 | .254 | .620 |
| Error(SNR) | | Linear | 5078.702 | 18 | 282.150 | | |
| | | Quadratic | 1773.115 | 18 | 98.506 | | |
| | | Cubic | 3562.022 | 18 | 197.890 | | |
| processing * SNR | Linear | Linear | 7773.407 | 1 | 7773.407 | 64.654 | .000 |
| | | Quadratic | 25.352 | 1 | 25.352 | .393 | .539 |
| | | Cubic | 5.461 | 1 | 5.461 | .032 | .861 |
| | Quadratic | Linear | 1347.607 | 1 | 1347.607 | 14.019 | .001 |
| | | Quadratic | 2952.716 | 1 | 2952.716 | 38.443 | .000 |
| | | Cubic | 59.574 | 1 | 59.574 | .321 | .578 |
| | Cubic | Linear | 1055.809 | 1 | 1055.809 | 11.125 | .004 |
| | | Quadratic | 128.362 | 1 | 128.362 | 1.125 | .303 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Cubic | 257.487 | 1 | 257.487 | 2.025 | .172 |
| processing * SNR * Group | Linear | Linear | 21.437 | 1 | 21.437 | .178 | .678 |
| | | Quadratic | 286.141 | 1 | 286.141 | 4.438 | .049 |
| | | Cubic | .086 | 1 | .086 | .000 | .983 |
| | Quadratic | Linear | 7.610 | 1 | 7.610 | .079 | .782 |
| | | Quadratic | 66.516 | 1 | 66.516 | .866 | .364 |
| | | Cubic | 35.361 | 1 | 35.361 | .191 | .668 |
| | Cubic | Linear | 10.253 | 1 | 10.253 | .108 | .746 |
| | | Quadratic | .817 | 1 | .817 | .007 | .933 |
| | | Cubic | 136.542 | 1 | 136.542 | 1.074 | .314 |
| Error(processing*SNR) | Linear | Linear | 2164.139 | 18 | 120.230 | | |
| | | Quadratic | 1160.674 | 18 | 64.482 | | |
| | | Cubic | 3117.086 | 18 | 173.171 | | |
| | Quadratic | Linear | 1730.273 | 18 | 96.126 | | |
| | | Quadratic | 1382.547 | 18 | 76.808 | | |
| | | Cubic | 3339.080 | 18 | 185.504 | | |
| | Cubic | Linear | 1708.295 | 18 | 94.905 | | |
| | | Quadratic | 2053.304 | 18 | 114.072 | | |
| | | Cubic | 2288.275 | 18 | 127.126 | | |

**Tests of Between-Subjects Effects**

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Intercept | 844177.285 | 1 | 844177.285 | 599.115 | .000 |
| Group | 5912.832 | 1 | 5912.832 | 4.196 | .055 |
| Error | 25362.717 | 18 | 1409.040 | | |

## Estimated Marginal Means

## 1. Group

**Estimates**

Measure: MEASURE_1

| Group | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| APD | 47.063 | 2.968 | 40.829 | 53.298 |
| NC | 55.661 | 2.968 | 49.426 | 61.895 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) Group | (J) Group | Mean Difference (I-J) | Std. Error | Sig.[a] | 95% Confidence Interval for Difference[a] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |

| | | | | | | |
|---|---|---|---|---|---|---|
| APD | NC | -8.597 | 4.197 | .055 | -17.414 | .220 |
| NC | APD | 8.597 | 4.197 | .055 | -.220 | 17.414 |

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

**Univariate Tests**

Measure: MEASURE_1

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 369.552 | 1 | 369.552 | 4.196 | .055 |
| Error | 1585.170 | 18 | 88.065 | | |

The F tests the effect of Group. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

## 2. processing

**Estimates**

Measure: MEASURE_1

| processing | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| 1 | 58.332 | 2.417 | 53.254 | 63.410 |
| 2 | 50.490 | 2.412 | 45.422 | 55.558 |
| 3 | 40.595 | 2.625 | 35.081 | 46.109 |
| 4 | 56.031 | 2.288 | 51.225 | 60.837 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|
| 1 | 2 | 7.842* | 2.259 | .016 | 1.148 | 14.536 |
| | 3 | 17.737* | 2.509 | .000 | 10.304 | 25.171 |
| | 4 | 2.301 | 2.064 | 1.000 | -3.815 | 8.417 |
| 2 | 1 | -7.842* | 2.259 | .016 | -14.536 | -1.148 |
| | 3 | 9.895* | 1.583 | .000 | 5.206 | 14.585 |
| | 4 | -5.541* | 1.752 | .032 | -10.732 | -.350 |
| 3 | 1 | -17.737* | 2.509 | .000 | -25.171 | -10.304 |
| | 2 | -9.895* | 1.583 | .000 | -14.585 | -5.206 |
| | 4 | -15.436* | 1.855 | .000 | -20.933 | -9.940 |
| 4 | 1 | -2.301 | 2.064 | 1.000 | -8.417 | 3.815 |
| | 2 | 5.541* | 1.752 | .032 | .350 | 10.732 |
| | 3 | 15.436* | 1.855 | .000 | 9.940 | 20.933 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .816 | 23.705[a] | 3.000 | 16.000 | .000 |
| Wilks' lambda | .184 | 23.705[a] | 3.000 | 16.000 | .000 |
| Hotelling's trace | 4.445 | 23.705[a] | 3.000 | 16.000 | .000 |
| Roy's largest root | 4.445 | 23.705[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate effect of processing. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

**3. Group * processing**

Measure: MEASURE_1

| Group | processing | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| APD | 1 | 49.184 | 3.418 | 42.003 | 56.366 |
| | 2 | 47.102 | 3.412 | 39.935 | 54.269 |
| | 3 | 37.806 | 3.712 | 30.008 | 45.604 |
| | 4 | 54.161 | 3.235 | 47.364 | 60.958 |
| NC | 1 | 67.479 | 3.418 | 60.298 | 74.660 |
| | 2 | 53.878 | 3.412 | 46.711 | 61.046 |
| | 3 | 43.383 | 3.712 | 35.585 | 51.181 |

| | | | | | |
|---|---|---|---|---|---|
| | 4 | 57.901 | 3.235 | 51.105 | 64.698 |

**4. Group * SNR**

Measure: MEASURE_1

| Group | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| APD | 1 | 79.662 | 3.032 | 73.292 | 86.031 |
| | 2 | 64.345 | 3.946 | 56.055 | 72.635 |
| | 3 | 37.004 | 3.255 | 30.165 | 43.842 |
| | 4 | 7.243 | 3.786 | -.710 | 15.197 |
| NC | 1 | 86.703 | 3.032 | 80.334 | 93.073 |
| | 2 | 75.018 | 3.946 | 66.728 | 83.309 |
| | 3 | 45.643 | 3.255 | 38.805 | 52.482 |
| | 4 | 15.277 | 3.786 | 7.324 | 23.231 |

**5. processing * SNR**

Measure: MEASURE_1

| processing | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| 1 | 1 | 104.321 | 2.905 | 98.218 | 110.424 |
| | 2 | 76.659 | 3.166 | 70.008 | 83.310 |

| | | | | | |
|---|---|---|---|---|---|
| | 3 | 40.889 | 3.927 | 32.639 | 49.138 |
| | 4 | 11.459 | 3.049 | 5.054 | 17.863 |
| 2 | 1 | 82.342 | 3.292 | 75.426 | 89.258 |
| | 2 | 72.772 | 3.424 | 65.578 | 79.966 |
| | 3 | 44.013 | 2.885 | 37.952 | 50.074 |
| | 4 | 2.834 | 3.335 | -4.171 | 9.840 |
| 3 | 1 | 60.416 | 2.905 | 54.314 | 66.519 |
| | 2 | 60.350 | 3.837 | 52.290 | 68.410 |
| | 3 | 33.748 | 3.279 | 26.860 | 40.637 |
| | 4 | 7.864 | 3.817 | -.155 | 15.884 |
| 4 | 1 | 85.650 | 2.894 | 79.571 | 91.730 |
| | 2 | 68.946 | 3.943 | 60.661 | 77.230 |
| | 3 | 46.644 | 2.638 | 41.103 | 52.186 |
| | 4 | 22.884 | 3.485 | 15.562 | 30.206 |

**6. Group * processing * SNR**

Measure: MEASURE_1

| Group | processing | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| APD | 1 | 1 | 96.663 | 4.108 | 88.032 | 105.294 |
| | | 2 | 65.504 | 4.477 | 56.098 | 74.910 |
| | | 3 | 31.019 | 5.553 | 19.352 | 42.685 |
| | | 4 | 3.552 | 4.311 | -5.506 | 12.610 |
| | 2 | 1 | 80.104 | 4.655 | 70.324 | 89.885 |
| | | 2 | 66.567 | 4.842 | 56.393 | 76.741 |
| | | 3 | 40.760 | 4.080 | 32.189 | 49.331 |
| | | 4 | .977 | 4.716 | -8.931 | 10.884 |
| | 3 | 1 | 58.233 | 4.108 | 49.603 | 66.863 |
| | | 2 | 58.145 | 5.426 | 46.746 | 69.544 |
| | | 3 | 29.116 | 4.637 | 19.374 | 38.858 |
| | | 4 | 5.732 | 5.398 | -5.609 | 17.073 |
| | 4 | 1 | 83.646 | 4.092 | 75.048 | 92.244 |
| | | 2 | 67.165 | 5.576 | 55.449 | 78.880 |
| | | 3 | 47.120 | 3.730 | 39.283 | 54.957 |
| | | 4 | 18.713 | 4.929 | 8.359 | 29.068 |
| NC | 1 | 1 | 111.979 | 4.108 | 103.348 | 120.610 |

| | | | | | |
|---|---|---|---|---|---|
| | 2 | 87.814 | 4.477 | 78.408 | 97.220 |
| | 3 | 50.759 | 5.553 | 39.092 | 62.426 |
| | 4 | 19.365 | 4.311 | 10.307 | 28.423 |
| 2 | 1 | 84.579 | 4.655 | 74.799 | 94.359 |
| | 2 | 78.977 | 4.842 | 68.803 | 89.151 |
| | 3 | 47.266 | 4.080 | 38.694 | 55.837 |
| | 4 | 4.692 | 4.716 | -5.215 | 14.599 |
| 3 | 1 | 62.599 | 4.108 | 53.969 | 71.230 |
| | 2 | 62.556 | 5.426 | 51.157 | 73.955 |
| | 3 | 38.381 | 4.637 | 28.639 | 48.123 |
| | 4 | 9.997 | 5.398 | -1.344 | 21.338 |
| 4 | 1 | 87.655 | 4.092 | 79.057 | 96.253 |
| | 2 | 70.727 | 5.576 | 59.011 | 82.443 |
| | 3 | 46.169 | 3.730 | 38.331 | 54.006 |
| | 4 | 27.055 | 4.929 | 16.700 | 37.410 |

## 7. processing * SNR

**Estimates**

Measure: MEASURE_1

| processing | SNR | Mean | Std. Error | 95% Confidence Interval Lower Bound | Upper Bound |
|---|---|---|---|---|---|
| 1 | 1 | 104.321 | 2.905 | 98.218 | 110.424 |
| | 2 | 76.659 | 3.166 | 70.008 | 83.310 |
| | 3 | 40.889 | 3.927 | 32.639 | 49.138 |
| | 4 | 11.459 | 3.049 | 5.054 | 17.863 |
| 2 | 1 | 82.342 | 3.292 | 75.426 | 89.258 |
| | 2 | 72.772 | 3.424 | 65.578 | 79.966 |
| | 3 | 44.013 | 2.885 | 37.952 | 50.074 |
| | 4 | 2.834 | 3.335 | -4.171 | 9.840 |
| 3 | 1 | 60.416 | 2.905 | 54.314 | 66.519 |
| | 2 | 60.350 | 3.837 | 52.290 | 68.410 |
| | 3 | 33.748 | 3.279 | 26.860 | 40.637 |
| | 4 | 7.864 | 3.817 | -.155 | 15.884 |
| 4 | 1 | 85.650 | 2.894 | 79.571 | 91.730 |
| | 2 | 68.946 | 3.943 | 60.661 | 77.230 |
| | 3 | 46.644 | 2.638 | 41.103 | 52.186 |
| | 4 | 22.884 | 3.485 | 15.562 | 30.206 |

**Pairwise Comparisons**

Measure: MEASURE_1

| SNR | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 21.979* | 4.639 | .001 | 8.234 | 35.724 |
| | | 3 | 43.905* | 3.908 | .000 | 32.327 | 55.483 |
| | | 4 | 18.670* | 2.819 | .000 | 10.319 | 27.022 |
| | 2 | 1 | -21.979* | 4.639 | .001 | -35.724 | -8.234 |
| | | 3 | 21.926* | 2.999 | .000 | 13.041 | 30.810 |
| | | 4 | -3.309 | 3.116 | 1.000 | -12.540 | 5.923 |
| | 3 | 1 | -43.905* | 3.908 | .000 | -55.483 | -32.327 |
| | | 2 | -21.926* | 2.999 | .000 | -30.810 | -13.041 |
| | | 4 | -25.234* | 2.714 | .000 | -33.276 | -17.193 |
| | 4 | 1 | -18.670* | 2.819 | .000 | -27.022 | -10.319 |
| | | 2 | 3.309 | 3.116 | 1.000 | -5.923 | 12.540 |
| | | 3 | 25.234* | 2.714 | .000 | 17.193 | 33.276 |
| 2 | 1 | 2 | 3.887 | 3.563 | 1.000 | -6.669 | 14.443 |
| | | 3 | 16.309* | 3.874 | .003 | 4.832 | 27.786 |
| | | 4 | 7.714 | 4.481 | .614 | -5.561 | 20.988 |
| | 2 | 1 | -3.887 | 3.563 | 1.000 | -14.443 | 6.669 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 3 | 12.422* | 3.255 | .008 | 2.778 | 22.066 |
| | | 4 | 3.826 | 3.557 | 1.000 | -6.711 | 14.364 |
| | 3 | 1 | -16.309* | 3.874 | .003 | -27.786 | -4.832 |
| | | 2 | -12.422* | 3.255 | .008 | -22.066 | -2.778 |
| | | 4 | -8.596 | 3.531 | .153 | -19.057 | 1.866 |
| | 4 | 1 | -7.714 | 4.481 | .614 | -20.988 | 5.561 |
| | | 2 | -3.826 | 3.557 | 1.000 | -14.364 | 6.711 |
| | | 3 | 8.596 | 3.531 | .153 | -1.866 | 19.057 |
| 3 | 1 | 2 | -3.124 | 3.652 | 1.000 | -13.944 | 7.696 |
| | | 3 | 7.140 | 4.251 | .662 | -5.455 | 19.736 |
| | | 4 | -5.756 | 3.383 | .636 | -15.777 | 4.266 |
| | 2 | 1 | 3.124 | 3.652 | 1.000 | -7.696 | 13.944 |
| | | 3 | 10.265 | 3.874 | .098 | -1.215 | 21.744 |
| | | 4 | -2.632 | 3.434 | 1.000 | -12.806 | 7.543 |
| | 3 | 1 | -7.140 | 4.251 | .662 | -19.736 | 5.455 |
| | | 2 | -10.265 | 3.874 | .098 | -21.744 | 1.215 |
| | | 4 | -12.896* | 3.374 | .007 | -22.892 | -2.900 |
| | 4 | 1 | 5.756 | 3.383 | .636 | -4.266 | 15.777 |
| | | 2 | 2.632 | 3.434 | 1.000 | -7.543 | 12.806 |
| | | 3 | 12.896* | 3.374 | .007 | 2.900 | 22.892 |
| 4 | 1 | 2 | 8.624 | 3.419 | .128 | -1.505 | 18.753 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 3 | 3.594 | 3.593 | 1.000 | -7.051 | 14.240 |
| | 4 | -11.426* | 3.797 | .045 | -22.674 | -.177 |
| 2 | 1 | -8.624 | 3.419 | .128 | -18.753 | 1.505 |
| | 3 | -5.030 | 2.826 | .552 | -13.403 | 3.343 |
| | 4 | -20.050* | 3.400 | .000 | -30.123 | -9.976 |
| 3 | 1 | -3.594 | 3.593 | 1.000 | -14.240 | 7.051 |
| | 2 | 5.030 | 2.826 | .552 | -3.343 | 13.403 |
| | 4 | -15.020* | 3.911 | .007 | -26.607 | -3.433 |
| 4 | 1 | 11.426* | 3.797 | .045 | .177 | 22.674 |
| | 2 | 20.050* | 3.400 | .000 | 9.976 | 30.123 |
| | 3 | 15.020* | 3.911 | .007 | 3.433 | 26.607 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| SNR | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| 1 | Pillai's trace | .901 | 48.365[a] | 3.000 | 16.000 | .000 |
| | Wilks' lambda | .099 | 48.365[a] | 3.000 | 16.000 | .000 |
| | Hotelling's trace | 9.068 | 48.365[a] | 3.000 | 16.000 | .000 |
| | Roy's largest root | 9.068 | 48.365[a] | 3.000 | 16.000 | .000 |
| 2 | Pillai's trace | .549 | 6.489[a] | 3.000 | 16.000 | .004 |
| | Wilks' lambda | .451 | 6.489[a] | 3.000 | 16.000 | .004 |
| | Hotelling's trace | 1.217 | 6.489[a] | 3.000 | 16.000 | .004 |
| | Roy's largest root | 1.217 | 6.489[a] | 3.000 | 16.000 | .004 |
| 3 | Pillai's trace | .480 | 4.915[a] | 3.000 | 16.000 | .013 |
| | Wilks' lambda | .520 | 4.915[a] | 3.000 | 16.000 | .013 |
| | Hotelling's trace | .922 | 4.915[a] | 3.000 | 16.000 | .013 |
| | Roy's largest root | .922 | 4.915[a] | 3.000 | 16.000 | .013 |
| 4 | Pillai's trace | .661 | 10.382[a] | 3.000 | 16.000 | .000 |
| | Wilks' lambda | .339 | 10.382[a] | 3.000 | 16.000 | .000 |
| | Hotelling's trace | 1.947 | 10.382[a] | 3.000 | 16.000 | .000 |
| | Roy's largest root | 1.947 | 10.382[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 8. Group * processing * SNR

**Estimates**

Measure: MEASURE_1

| Group | processing | SNR | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|
| APD | 1 | 1 | 96.663 | 4.108 | 88.032 | 105.294 |
| | | 2 | 65.504 | 4.477 | 56.098 | 74.910 |
| | | 3 | 31.019 | 5.553 | 19.352 | 42.685 |
| | | 4 | 3.552 | 4.311 | -5.506 | 12.610 |
| | 2 | 1 | 80.104 | 4.655 | 70.324 | 89.885 |
| | | 2 | 66.567 | 4.842 | 56.393 | 76.741 |
| | | 3 | 40.760 | 4.080 | 32.189 | 49.331 |
| | | 4 | .977 | 4.716 | -8.931 | 10.884 |
| | 3 | 1 | 58.233 | 4.108 | 49.603 | 66.863 |
| | | 2 | 58.145 | 5.426 | 46.746 | 69.544 |
| | | 3 | 29.116 | 4.637 | 19.374 | 38.858 |
| | | 4 | 5.732 | 5.398 | -5.609 | 17.073 |
| | 4 | 1 | 83.646 | 4.092 | 75.048 | 92.244 |
| | | 2 | 67.165 | 5.576 | 55.449 | 78.880 |
| | | 3 | 47.120 | 3.730 | 39.283 | 54.957 |
| | | 4 | 18.713 | 4.929 | 8.359 | 29.068 |

| | | | | | | |
|---|---|---|---|---|---|---|
| NC | 1 | 1 | 111.979 | 4.108 | 103.348 | 120.610 |
| | | 2 | 87.814 | 4.477 | 78.408 | 97.220 |
| | | 3 | 50.759 | 5.553 | 39.092 | 62.426 |
| | | 4 | 19.365 | 4.311 | 10.307 | 28.423 |
| | 2 | 1 | 84.579 | 4.655 | 74.799 | 94.359 |
| | | 2 | 78.977 | 4.842 | 68.803 | 89.151 |
| | | 3 | 47.266 | 4.080 | 38.694 | 55.837 |
| | | 4 | 4.692 | 4.716 | -5.215 | 14.599 |
| | 3 | 1 | 62.599 | 4.108 | 53.969 | 71.230 |
| | | 2 | 62.556 | 5.426 | 51.157 | 73.955 |
| | | 3 | 38.381 | 4.637 | 28.639 | 48.123 |
| | | 4 | 9.997 | 5.398 | -1.344 | 21.338 |
| | 4 | 1 | 87.655 | 4.092 | 79.057 | 96.253 |
| | | 2 | 70.727 | 5.576 | 59.011 | 82.443 |
| | | 3 | 46.169 | 3.730 | 38.331 | 54.006 |
| | | 4 | 27.055 | 4.929 | 16.700 | 37.410 |

**Pairwise Comparisons**

Measure: MEASURE_1

| Group | SNR | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Lower Bound | Upper Bound |
| APD | 1 | 1 | 2 | 16.558 | 6.561 | .127 | -2.880 | 35.997 |
| | | | 3 | 38.430* | 5.527 | .000 | 22.056 | 54.804 |
| | | | 4 | 13.017* | 3.987 | .026 | 1.206 | 24.828 |
| | | 2 | 1 | -16.558 | 6.561 | .127 | -35.997 | 2.880 |
| | | | 3 | 21.871* | 4.241 | .000 | 9.306 | 34.436 |
| | | | 4 | -3.541 | 4.407 | 1.000 | -16.597 | 9.514 |
| | | 3 | 1 | -38.430* | 5.527 | .000 | -54.804 | -22.056 |
| | | | 2 | -21.871* | 4.241 | .000 | -34.436 | -9.306 |
| | | | 4 | -25.413* | 3.838 | .000 | -36.785 | -14.040 |
| | | 4 | 1 | -13.017* | 3.987 | .026 | -24.828 | -1.206 |
| | | | 2 | 3.541 | 4.407 | 1.000 | -9.514 | 16.597 |
| | | | 3 | 25.413* | 3.838 | .000 | 14.040 | 36.785 |
| | 2 | 1 | 2 | -1.062 | 5.039 | 1.000 | -15.991 | 13.866 |
| | | | 3 | 7.360 | 5.478 | 1.000 | -8.871 | 23.591 |
| | | | 4 | -1.660 | 6.337 | 1.000 | -20.434 | 17.113 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2 | 1 | 1.062 | 5.039 | 1.000 | -13.866 | 15.991 |
| | | 3 | 8.422 | 4.603 | .504 | -5.217 | 22.061 |
| | | 4 | -.598 | 5.030 | 1.000 | -15.500 | 14.304 |
| | 3 | 1 | -7.360 | 5.478 | 1.000 | -23.591 | 8.871 |
| | | 2 | -8.422 | 4.603 | .504 | -22.061 | 5.217 |
| | | 4 | -9.020 | 4.994 | .526 | -23.815 | 5.775 |
| | 4 | 1 | 1.660 | 6.337 | 1.000 | -17.113 | 20.434 |
| | | 2 | .598 | 5.030 | 1.000 | -14.304 | 15.500 |
| | | 3 | 9.020 | 4.994 | .526 | -5.775 | 23.815 |
| 3 | 1 | 2 | -9.741 | 5.165 | .453 | -25.043 | 5.561 |
| | | 3 | 1.903 | 6.012 | 1.000 | -15.910 | 19.715 |
| | | 4 | -16.101* | 4.784 | .021 | -30.274 | -1.928 |
| | 2 | 1 | 9.741 | 5.165 | .453 | -5.561 | 25.043 |
| | | 3 | 11.644 | 5.479 | .286 | -4.590 | 27.878 |
| | | 4 | -6.360 | 4.857 | 1.000 | -20.749 | 8.029 |
| | 3 | 1 | -1.903 | 6.012 | 1.000 | -19.715 | 15.910 |
| | | 2 | -11.644 | 5.479 | .286 | -27.878 | 4.590 |
| | | 4 | -18.004* | 4.772 | .008 | -32.141 | -3.867 |
| | 4 | 1 | 16.101* | 4.784 | .021 | 1.928 | 30.274 |
| | | 2 | 6.360 | 4.857 | 1.000 | -8.029 | 20.749 |
| | | 3 | 18.004* | 4.772 | .008 | 3.867 | 32.141 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 4 | 1 | 2 | 2.575 | 4.835 | 1.000 | -11.750 | 16.900 |
| | | | 3 | -2.180 | 5.081 | 1.000 | -17.235 | 12.875 |
| | | | 4 | -15.162 | 5.369 | .067 | -31.069 | .746 |
| | | 2 | 1 | -2.575 | 4.835 | 1.000 | -16.900 | 11.750 |
| | | | 3 | -4.755 | 3.997 | 1.000 | -16.597 | 7.087 |
| | | | 4 | -17.737* | 4.808 | .010 | -31.983 | -3.491 |
| | | 3 | 1 | 2.180 | 5.081 | 1.000 | -12.875 | 17.235 |
| | | | 2 | 4.755 | 3.997 | 1.000 | -7.087 | 16.597 |
| | | | 4 | -12.982 | 5.531 | .183 | -29.368 | 3.405 |
| | | 4 | 1 | 15.162 | 5.369 | .067 | -.746 | 31.069 |
| | | | 2 | 17.737* | 4.808 | .010 | 3.491 | 31.983 |
| | | | 3 | 12.982 | 5.531 | .183 | -3.405 | 29.368 |
| NC | 1 | 1 | 2 | 27.400* | 6.561 | .003 | 7.962 | 46.838 |
| | | | 3 | 49.380* | 5.527 | .000 | 33.006 | 65.753 |
| | | | 4 | 24.324* | 3.987 | .000 | 12.512 | 36.135 |
| | | 2 | 1 | -27.400* | 6.561 | .003 | -46.838 | -7.962 |
| | | | 3 | 21.980* | 4.241 | .000 | 9.415 | 34.545 |
| | | | 4 | -3.076 | 4.407 | 1.000 | -16.132 | 9.979 |
| | | 3 | 1 | -49.380* | 5.527 | .000 | -65.753 | -33.006 |
| | | | 2 | -21.980* | 4.241 | .000 | -34.545 | -9.415 |
| | | | 4 | -25.056* | 3.838 | .000 | -36.428 | -13.684 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 4 | 1 | -24.324* | 3.987 | .000 | -36.135 | -12.512 |
| | | 2 | 3.076 | 4.407 | 1.000 | -9.979 | 16.132 |
| | | 3 | 25.056* | 3.838 | .000 | 13.684 | 36.428 |
| 2 | 1 | 2 | 8.837 | 5.039 | .579 | -6.091 | 23.766 |
| | | 3 | 25.259* | 5.478 | .001 | 9.027 | 41.490 |
| | | 4 | 17.087 | 6.337 | .089 | -1.686 | 35.861 |
| | 2 | 1 | -8.837 | 5.039 | .579 | -23.766 | 6.091 |
| | | 3 | 16.421* | 4.603 | .013 | 2.783 | 30.060 |
| | | 4 | 8.250 | 5.030 | .710 | -6.652 | 23.152 |
| | 3 | 1 | -25.259* | 5.478 | .001 | -41.490 | -9.027 |
| | | 2 | -16.421* | 4.603 | .013 | -30.060 | -2.783 |
| | | 4 | -8.171 | 4.994 | .715 | -22.966 | 6.623 |
| | 4 | 1 | -17.087 | 6.337 | .089 | -35.861 | 1.686 |
| | | 2 | -8.250 | 5.030 | .710 | -23.152 | 6.652 |
| | | 3 | 8.171 | 4.994 | .715 | -6.623 | 22.966 |
| 3 | 1 | 2 | 3.493 | 5.165 | 1.000 | -11.809 | 18.795 |
| | | 3 | 12.378 | 6.012 | .326 | -5.435 | 30.191 |
| | | 4 | 4.590 | 4.784 | 1.000 | -9.583 | 18.763 |
| | 2 | 1 | -3.493 | 5.165 | 1.000 | -18.795 | 11.809 |
| | | 3 | 8.885 | 5.479 | .734 | -7.349 | 25.119 |
| | | 4 | 1.097 | 4.857 | 1.000 | -13.292 | 15.485 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 3 | 1 | -12.378 | 6.012 | .326 | -30.191 | 5.435 |
| | | 2 | -8.885 | 5.479 | .734 | -25.119 | 7.349 |
| | | 4 | -7.788 | 4.772 | .720 | -21.925 | 6.349 |
| | 4 | 1 | -4.590 | 4.784 | 1.000 | -18.763 | 9.583 |
| | | 2 | -1.097 | 4.857 | 1.000 | -15.485 | 13.292 |
| | | 3 | 7.788 | 4.772 | .720 | -6.349 | 21.925 |
| 4 | 1 | 2 | 14.673* | 4.835 | .043 | .348 | 28.998 |
| | | 3 | 9.368 | 5.081 | .491 | -5.687 | 24.423 |
| | | 4 | -7.690 | 5.369 | 1.000 | -23.597 | 8.218 |
| | 2 | 1 | -14.673* | 4.835 | .043 | -28.998 | -.348 |
| | | 3 | -5.305 | 3.997 | 1.000 | -17.147 | 6.537 |
| | | 4 | -22.363* | 4.808 | .001 | -36.609 | -8.117 |
| | 3 | 1 | -9.368 | 5.081 | .491 | -24.423 | 5.687 |
| | | 2 | 5.305 | 3.997 | 1.000 | -6.537 | 17.147 |
| | | 4 | -17.058* | 5.531 | .038 | -33.444 | -.671 |
| | 4 | 1 | 7.690 | 5.369 | 1.000 | -8.218 | 23.597 |
| | | 2 | 22.363* | 4.808 | .001 | 8.117 | 36.609 |
| | | 3 | 17.058* | 5.531 | .038 | .671 | 33.444 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| Group | SNR | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|---|
| APD | 1 | Pillai's trace | .790 | 20.089[a] | 3.000 | 16.000 | .000 |
| | | Wilks' lambda | .210 | 20.089[a] | 3.000 | 16.000 | .000 |
| | | Hotelling's trace | 3.767 | 20.089[a] | 3.000 | 16.000 | .000 |
| | | Roy's largest root | 3.767 | 20.089[a] | 3.000 | 16.000 | .000 |
| | 2 | Pillai's trace | .208 | 1.400[a] | 3.000 | 16.000 | .279 |
| | | Wilks' lambda | .792 | 1.400[a] | 3.000 | 16.000 | .279 |
| | | Hotelling's trace | .263 | 1.400[a] | 3.000 | 16.000 | .279 |
| | | Roy's largest root | .263 | 1.400[a] | 3.000 | 16.000 | .279 |
| | 3 | Pillai's trace | .555 | 6.655[a] | 3.000 | 16.000 | .004 |
| | | Wilks' lambda | .445 | 6.655[a] | 3.000 | 16.000 | .004 |
| | | Hotelling's trace | 1.248 | 6.655[a] | 3.000 | 16.000 | .004 |
| | | Roy's largest root | 1.248 | 6.655[a] | 3.000 | 16.000 | .004 |
| | 4 | Pillai's trace | .454 | 4.435[a] | 3.000 | 16.000 | .019 |
| | | Wilks' lambda | .546 | 4.435[a] | 3.000 | 16.000 | .019 |
| | | Hotelling's trace | .831 | 4.435[a] | 3.000 | 16.000 | .019 |
| | | Roy's largest root | .831 | 4.435[a] | 3.000 | 16.000 | .019 |
| NC | 1 | Pillai's trace | .847 | 29.566[a] | 3.000 | 16.000 | .000 |
| | | Wilks' lambda | .153 | 29.566[a] | 3.000 | 16.000 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Hotelling's trace | 5.544 | 29.566[a] | 3.000 | 16.000 | .000 |
| | Roy's largest root | 5.544 | 29.566[a] | 3.000 | 16.000 | .000 |
| 2 | Pillai's trace | .564 | 6.890[a] | 3.000 | 16.000 | .003 |
| | Wilks' lambda | .436 | 6.890[a] | 3.000 | 16.000 | .003 |
| | Hotelling's trace | 1.292 | 6.890[a] | 3.000 | 16.000 | .003 |
| | Roy's largest root | 1.292 | 6.890[a] | 3.000 | 16.000 | .003 |
| 3 | Pillai's trace | .202 | 1.353[a] | 3.000 | 16.000 | .293 |
| | Wilks' lambda | .798 | 1.353[a] | 3.000 | 16.000 | .293 |
| | Hotelling's trace | .254 | 1.353[a] | 3.000 | 16.000 | .293 |
| | Roy's largest root | .254 | 1.353[a] | 3.000 | 16.000 | .293 |
| 4 | Pillai's trace | .566 | 6.968[a] | 3.000 | 16.000 | .003 |
| | Wilks' lambda | .434 | 6.968[a] | 3.000 | 16.000 | .003 |
| | Hotelling's trace | 1.306 | 6.968[a] | 3.000 | 16.000 | .003 |
| | Roy's largest root | 1.306 | 6.968[a] | 3.000 | 16.000 | .003 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

Non- Stationary Background Noise Experiment

## General Linear Model

**Notes**

| | | |
|---|---|---|
| Output Created | | 13-DEC-2018 08:59:46 |
| Comments | | |
| Input | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 10 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing. |
| | Cases Used | Statistics are based on all cases with valid data for all variables in the model. |

| | | |
|---|---|---|
| Syntax | | GLM UP_4 UP_0 UP_3 UP_6 SEE_4 SEE_0 SEE_3 SEE_6 MMSESEE_4 MMSESEE_0 MMSESEE_3 MMSESEE_6 MHASEE_4<br>MHASEE_0 MHASEE_3 MHASEE_6<br>/WSFACTOR=processing 4 Polynomial SNR 4 Polynomial<br>/METHOD=SSTYPE(3)<br>/EMMEANS=TABLES(OVERALL)<br>/EMMEANS=TABLES(processing) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(SNR) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(processing*SNR) COMPARE(processing)ADJ(BONFERRONI)<br>/CRITERIA=ALPHA(.05)<br>/WSDESIGN=processing SNR processing*SNR. |
| Resources | Processor Time | 00:00:00.08 |
| | Elapsed Time | 00:00:00.06 |

[DataSet1]

**Within-Subjects Factors**

Measure: MEASURE_1

| processing | SNR | Dependent Variable |
|---|---|---|
| 1 | 1 | UP_4 |
| | 2 | UP_0 |
| | 3 | UP_3 |
| | 4 | UP_6 |
| 2 | 1 | SEE_4 |
| | 2 | SEE_0 |
| | 3 | SEE_3 |
| | 4 | SEE_6 |
| 3 | 1 | MMSESEE_4 |
| | 2 | MMSESEE_0 |
| | 3 | MMSESEE_3 |
| | 4 | MMSESEE_6 |
| 4 | 1 | MHASEE_4 |
| | 2 | MHASEE_0 |
| | 3 | MHASEE_3 |
| | 4 | MHASEE_6 |

**Multivariate Tests[a]**

| Effect | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| processing | Pillai's Trace | .973 | 82.616[b] | 3.000 | 7.000 | .000 |
| | Wilks' Lambda | .027 | 82.616[b] | 3.000 | 7.000 | .000 |
| | Hotelling's Trace | 35.407 | 82.616[b] | 3.000 | 7.000 | .000 |
| | Roy's Largest Root | 35.407 | 82.616[b] | 3.000 | 7.000 | .000 |
| SNR | Pillai's Trace | .987 | 180.865[b] | 3.000 | 7.000 | .000 |
| | Wilks' Lambda | .013 | 180.865[b] | 3.000 | 7.000 | .000 |
| | Hotelling's Trace | 77.513 | 180.865[b] | 3.000 | 7.000 | .000 |
| | Roy's Largest Root | 77.513 | 180.865[b] | 3.000 | 7.000 | .000 |
| processing * SNR | Pillai's Trace | .999 | 111.720[b] | 9.000 | 1.000 | .073 |
| | Wilks' Lambda | .001 | 111.720[b] | 9.000 | 1.000 | .073 |
| | Hotelling's Trace | 1005.478 | 111.720[b] | 9.000 | 1.000 | .073 |
| | Roy's Largest Root | 1005.478 | 111.720[b] | 9.000 | 1.000 | .073 |

a. Design: Intercept

Within Subjects Design: processing + SNR + processing * SNR

b. Exact statistic

**Mauchly's Test of Sphericity[a]**

Measure: MEASURE_1

| Within Subjects Effect | Mauchly's W | Approx. Chi-Square | df | Sig. | Epsilon[b] | | |
|---|---|---|---|---|---|---|---|
| | | | | | Greenhouse-Geisser | Huynh-Feldt | Lower-bound |
| processing | .566 | 4.402 | 5 | .496 | .746 | 1.000 | .333 |
| SNR | .369 | 7.694 | 5 | .177 | .596 | .734 | .333 |
| processing * SNR | .000 | 54.582 | 44 | .298 | .472 | .945 | .111 |

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept

Within Subjects Design: processing + SNR + processing * SNR

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

**Tests of Within-Subjects Effects**

Measure: MEASURE_1

| Source | | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| processing | Sphericity Assumed | 29565.589 | 3 | 9855.196 | 81.037 | .000 |
| | Greenhouse-Geisser | 29565.589 | 2.238 | 13208.493 | 81.037 | .000 |
| | Huynh-Feldt | 29565.589 | 3.000 | 9855.196 | 81.037 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Lower-bound | 29565.589 | 1.000 | 29565.589 | 81.037 | .000 |
| Error(processing) | Sphericity Assumed | 3283.565 | 27 | 121.614 | | |
| | Greenhouse-Geisser | 3283.565 | 20.145 | 162.993 | | |
| | Huynh-Feldt | 3283.565 | 27.000 | 121.614 | | |
| | Lower-bound | 3283.565 | 9.000 | 364.841 | | |
| SNR | Sphericity Assumed | 109311.493 | 3 | 36437.164 | 243.319 | .000 |
| | Greenhouse-Geisser | 109311.493 | 1.788 | 61146.703 | 243.319 | .000 |
| | Huynh-Feldt | 109311.493 | 2.201 | 49656.227 | 243.319 | .000 |
| | Lower-bound | 109311.493 | 1.000 | 109311.493 | 243.319 | .000 |
| Error(SNR) | Sphericity Assumed | 4043.264 | 27 | 149.751 | | |
| | Greenhouse-Geisser | 4043.264 | 16.089 | 251.303 | | |
| | Huynh-Feldt | 4043.264 | 19.812 | 204.079 | | |
| | Lower-bound | 4043.264 | 9.000 | 449.252 | | |
| processing * SNR | Sphericity Assumed | 10697.521 | 9 | 1188.613 | 9.544 | .000 |
| | Greenhouse-Geisser | 10697.521 | 4.244 | 2520.690 | 9.544 | .000 |
| | Huynh-Feldt | 10697.521 | 8.503 | 1258.161 | 9.544 | .000 |
| | Lower-bound | 10697.521 | 1.000 | 10697.521 | 9.544 | .013 |
| Error(processing*SNR) | Sphericity Assumed | 10087.368 | 81 | 124.535 | | |
| | Greenhouse-Geisser | 10087.368 | 38.195 | 264.102 | | |
| | Huynh-Feldt | 10087.368 | 76.523 | 131.822 | | |
| | Lower-bound | 10087.368 | 9.000 | 1120.819 | | |

**Tests of Within-Subjects Contrasts**

Measure: MEASURE_1

| Source | processing | SNR | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| processing | Linear | | 26448.640 | 1 | 26448.640 | 172.349 | .000 |
| | Quadratic | | 2654.156 | 1 | 2654.156 | 21.361 | .001 |
| | Cubic | | 462.794 | 1 | 462.794 | 5.312 | .047 |
| Error(processing) | Linear | | 1381.140 | 9 | 153.460 | | |
| | Quadratic | | 1118.262 | 9 | 124.251 | | |
| | Cubic | | 784.163 | 9 | 87.129 | | |
| SNR | | Linear | 107783.413 | 1 | 107783.413 | 445.910 | .000 |
| | | Quadratic | 981.985 | 1 | 981.985 | 7.713 | .021 |
| | | Cubic | 546.095 | 1 | 546.095 | 6.807 | .028 |
| Error(SNR) | | Linear | 2175.443 | 9 | 241.716 | | |
| | | Quadratic | 1145.808 | 9 | 127.312 | | |
| | | Cubic | 722.014 | 9 | 80.224 | | |
| processing * SNR | Linear | Linear | 5198.708 | 1 | 5198.708 | 97.040 | .000 |
| | | Quadratic | 1752.146 | 1 | 1752.146 | 12.640 | .006 |
| | | Cubic | 277.241 | 1 | 277.241 | 2.197 | .172 |
| | Quadratic | Linear | 79.602 | 1 | 79.602 | 1.147 | .312 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Quadratic | 143.971 | 1 | 143.971 | .552 | .477 |
| | | Cubic | 2407.413 | 1 | 2407.413 | 19.284 | .002 |
| | Cubic | Linear | 642.230 | 1 | 642.230 | 5.151 | .049 |
| | | Quadratic | 165.071 | 1 | 165.071 | 2.088 | .182 |
| | | Cubic | 31.140 | 1 | 31.140 | .217 | .652 |
| Error(processing*SNR) | Linear | Linear | 482.158 | 9 | 53.573 | | |
| | | Quadratic | 1247.553 | 9 | 138.617 | | |
| | | Cubic | 1135.483 | 9 | 126.165 | | |
| | Quadratic | Linear | 624.491 | 9 | 69.388 | | |
| | | Quadratic | 2348.841 | 9 | 260.982 | | |
| | | Cubic | 1123.576 | 9 | 124.842 | | |
| | Cubic | Linear | 1122.098 | 9 | 124.678 | | |
| | | Quadratic | 711.425 | 9 | 79.047 | | |
| | | Cubic | 1291.744 | 9 | 143.527 | | |

**Tests of Between-Subjects Effects**

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Intercept | 79439.373 | 1 | 79439.373 | 30.776 | .000 |
| Error | 23230.942 | 9 | 2581.216 | | |

## Estimated Marginal Means

**1. Grand Mean**

Measure: MEASURE_1

| Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|
| | | Lower Bound | Upper Bound |
| 22.282 | 4.017 | 13.196 | 31.368 |

## 2. processing

**Estimates**

Measure: MEASURE_1

| processing | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|
| 1 | 44.365 | 4.791 | 33.527 | 55.204 |
| 2 | 21.677 | 4.909 | 10.573 | 32.781 |
| 3 | 14.741 | 3.749 | 6.260 | 23.223 |
| 4 | 8.345 | 3.542 | .333 | 16.357 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | 95% Confidence Interval for Difference[b] Upper Bound |
|---|---|---|---|---|---|---|
| 1 | 2 | 22.688* | 2.069 | .000 | 15.726 | 29.650 |
| | 3 | 29.624* | 3.193 | .000 | 18.884 | 40.364 |
| | 4 | 36.020* | 2.313 | .000 | 28.240 | 43.800 |
| 2 | 1 | -22.688* | 2.069 | .000 | -29.650 | -15.726 |
| | 3 | 6.936 | 2.585 | .150 | -1.760 | 15.632 |
| | 4 | 13.332* | 2.385 | .002 | 5.309 | 21.355 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | 1 | -29.624* | 3.193 | .000 | -40.364 | -18.884 |
| | 2 | -6.936 | 2.585 | .150 | -15.632 | 1.760 |
| | 4 | 6.396 | 2.072 | .078 | -.574 | 13.366 |
| 4 | 1 | -36.020* | 2.313 | .000 | -43.800 | -28.240 |
| | 2 | -13.332* | 2.385 | .002 | -21.355 | -5.309 |
| | 3 | -6.396 | 2.072 | .078 | -13.366 | .574 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .973 | 82.616[a] | 3.000 | 7.000 | .000 |
| Wilks' lambda | .027 | 82.616[a] | 3.000 | 7.000 | .000 |
| Hotelling's trace | 35.407 | 82.616[a] | 3.000 | 7.000 | .000 |
| Roy's largest root | 35.407 | 82.616[a] | 3.000 | 7.000 | .000 |

Each F tests the multivariate effect of processing. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 3. SNR

**Estimates**

Measure: MEASURE_1

| SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| 1 | 60.408 | 5.604 | 47.729 | 73.086 |
| 2 | 28.933 | 3.357 | 21.340 | 36.527 |
| 3 | 10.676 | 4.312 | .923 | 20.430 |
| 4 | -10.889 | 3.807 | -19.500 | -2.277 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) SNR | (J) SNR | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| 1 | 2 | 31.474* | 3.211 | .000 | 20.672 | 42.277 |
| | 3 | 49.732* | 3.532 | .000 | 37.850 | 61.613 |
| | 4 | 71.296* | 3.530 | .000 | 59.421 | 83.172 |
| 2 | 1 | -31.474* | 3.211 | .000 | -42.277 | -20.672 |
| | 3 | 18.257* | 1.907 | .000 | 11.842 | 24.673 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 4 | 39.822* | 1.669 | .000 | 34.207 | 45.437 |
| 3 | 1 | -49.732* | 3.532 | .000 | -61.613 | -37.850 |
| | 2 | -18.257* | 1.907 | .000 | -24.673 | -11.842 |
| | 4 | 21.565* | 1.805 | .000 | 15.493 | 27.637 |
| 4 | 1 | -71.296* | 3.530 | .000 | -83.172 | -59.421 |
| | 2 | -39.822* | 1.669 | .000 | -45.437 | -34.207 |
| | 3 | -21.565* | 1.805 | .000 | -27.637 | -15.493 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .987 | 180.865[a] | 3.000 | 7.000 | .000 |
| Wilks' lambda | .013 | 180.865[a] | 3.000 | 7.000 | .000 |
| Hotelling's trace | 77.513 | 180.865[a] | 3.000 | 7.000 | .000 |
| Roy's largest root | 77.513 | 180.865[a] | 3.000 | 7.000 | .000 |

Each F tests the multivariate effect of SNR. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 4. processing * SNR

**Estimates**

Measure: MEASURE_1

| processing | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| 1 | 1 | 90.090 | 5.335 | 78.021 | 102.159 |
| | 2 | 57.896 | 5.017 | 46.547 | 69.244 |
| | 3 | 37.565 | 5.739 | 24.583 | 50.548 |
| | 4 | -8.090 | 5.435 | -20.385 | 4.205 |
| 2 | 1 | 57.239 | 7.317 | 40.686 | 73.792 |
| | 2 | 33.908 | 7.871 | 16.103 | 51.713 |
| | 3 | 2.829 | 5.314 | -9.191 | 14.849 |
| | 4 | -7.267 | 4.333 | -17.069 | 2.536 |
| 3 | 1 | 51.966 | 5.737 | 38.988 | 64.943 |
| | 2 | 23.694 | 2.565 | 17.891 | 29.496 |
| | 3 | -1.298 | 5.003 | -12.614 | 10.019 |
| | 4 | -15.397 | 3.349 | -22.972 | -7.822 |
| 4 | 1 | 42.336 | 6.395 | 27.869 | 56.803 |
| | 2 | .237 | .042 | .142 | .331 |
| | 3 | 3.608 | 6.138 | -10.278 | 17.494 |
| | 4 | -12.801 | 4.323 | -22.580 | -3.021 |

**Pairwise Comparisons**

Measure: MEASURE_1

| SNR | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| 1 | 1 | 2 | 32.851* | 3.629 | .000 | 20.641 | 45.061 |
| | | 3 | 38.124* | 4.693 | .000 | 22.336 | 53.913 |
| | | 4 | 47.754* | 3.549 | .000 | 35.816 | 59.692 |
| | 2 | 1 | -32.851* | 3.629 | .000 | -45.061 | -20.641 |
| | | 3 | 5.274 | 5.896 | 1.000 | -14.560 | 25.107 |
| | | 4 | 14.903 | 4.971 | .090 | -1.820 | 31.626 |
| | 3 | 1 | -38.124* | 4.693 | .000 | -53.913 | -22.336 |
| | | 2 | -5.274 | 5.896 | 1.000 | -25.107 | 14.560 |
| | | 4 | 9.629 | 3.670 | .166 | -2.718 | 21.977 |
| | 4 | 1 | -47.754* | 3.549 | .000 | -59.692 | -35.816 |
| | | 2 | -14.903 | 4.971 | .090 | -31.626 | 1.820 |
| | | 3 | -9.629 | 3.670 | .166 | -21.977 | 2.718 |
| 2 | 1 | 2 | 23.988* | 7.103 | .049 | .092 | 47.884 |
| | | 3 | 34.202* | 4.475 | .000 | 19.148 | 49.256 |
| | | 4 | 57.659* | 4.993 | .000 | 40.863 | 74.456 |
| | 2 | 1 | -23.988* | 7.103 | .049 | -47.884 | -.092 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 3 | 10.214 | 5.573 | .600 | -8.535 | 28.963 |
| | | 4 | 33.671* | 7.847 | .012 | 7.271 | 60.071 |
| | 3 | 1 | -34.202* | 4.475 | .000 | -49.256 | -19.148 |
| | | 2 | -10.214 | 5.573 | .600 | -28.963 | 8.535 |
| | | 4 | 23.457* | 2.536 | .000 | 14.925 | 31.989 |
| | 4 | 1 | -57.659* | 4.993 | .000 | -74.456 | -40.863 |
| | | 2 | -33.671* | 7.847 | .012 | -60.071 | -7.271 |
| | | 3 | -23.457* | 2.536 | .000 | -31.989 | -14.925 |
| 3 | 1 | 2 | 34.736* | 5.386 | .001 | 16.615 | 52.856 |
| | | 3 | 38.863* | 5.996 | .001 | 18.690 | 59.035 |
| | | 4 | 33.957* | 5.895 | .002 | 14.124 | 53.790 |
| | 2 | 1 | -34.736* | 5.386 | .001 | -52.856 | -16.615 |
| | | 3 | 4.127 | 5.100 | 1.000 | -13.031 | 21.285 |
| | | 4 | -.778 | 5.736 | 1.000 | -20.076 | 18.519 |
| | 3 | 1 | -38.863* | 5.996 | .001 | -59.035 | -18.690 |
| | | 2 | -4.127 | 5.100 | 1.000 | -21.285 | 13.031 |
| | | 4 | -4.905 | 6.278 | 1.000 | -26.027 | 16.216 |
| | 4 | 1 | -33.957* | 5.895 | .002 | -53.790 | -14.124 |
| | | 2 | .778 | 5.736 | 1.000 | -18.519 | 20.076 |
| | | 3 | 4.905 | 6.278 | 1.000 | -16.216 | 26.027 |
| 4 | 1 | 2 | -.823 | 4.161 | 1.000 | -14.822 | 13.175 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 3 | 7.307 | 5.144 | 1.000 | -9.997 | 24.611 |
| | 4 | 4.711 | 2.608 | .626 | -4.064 | 13.485 |
| 2 | 1 | .823 | 4.161 | 1.000 | -13.175 | 14.822 |
| | 3 | 8.130 | 3.215 | .194 | -2.684 | 18.944 |
| | 4 | 5.534 | 2.118 | .169 | -1.593 | 12.660 |
| 3 | 1 | -7.307 | 5.144 | 1.000 | -24.611 | 9.997 |
| | 2 | -8.130 | 3.215 | .194 | -18.944 | 2.684 |
| | 4 | -2.596 | 3.951 | 1.000 | -15.889 | 10.697 |
| 4 | 1 | -4.711 | 2.608 | .626 | -13.485 | 4.064 |
| | 2 | -5.534 | 2.118 | .169 | -12.660 | 1.593 |
| | 3 | 2.596 | 3.951 | 1.000 | -10.697 | 15.889 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| SNR | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| 1 | Pillai's trace | .966 | 65.758[a] | 3.000 | 7.000 | .000 |
| | Wilks' lambda | .034 | 65.758[a] | 3.000 | 7.000 | .000 |
| | Hotelling's trace | 28.182 | 65.758[a] | 3.000 | 7.000 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Roy's largest root | 28.182 | 65.758[a] | 3.000 | 7.000 | .000 |
| 2 | Pillai's trace | .972 | 82.380[a] | 3.000 | 7.000 | .000 |
| | Wilks' lambda | .028 | 82.380[a] | 3.000 | 7.000 | .000 |
| | Hotelling's trace | 35.306 | 82.380[a] | 3.000 | 7.000 | .000 |
| | Roy's largest root | 35.306 | 82.380[a] | 3.000 | 7.000 | .000 |
| 3 | Pillai's trace | .865 | 14.967[a] | 3.000 | 7.000 | .002 |
| | Wilks' lambda | .135 | 14.967[a] | 3.000 | 7.000 | .002 |
| | Hotelling's trace | 6.414 | 14.967[a] | 3.000 | 7.000 | .002 |
| | Roy's largest root | 6.414 | 14.967[a] | 3.000 | 7.000 | .002 |
| 4 | Pillai's trace | .788 | 8.672[a] | 3.000 | 7.000 | .009 |
| | Wilks' lambda | .212 | 8.672[a] | 3.000 | 7.000 | .009 |
| | Hotelling's trace | 3.717 | 8.672[a] | 3.000 | 7.000 | .009 |
| | Roy's largest root | 3.717 | 8.672[a] | 3.000 | 7.000 | .009 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

# Appendix D: Dichotic Processing Speech Intelligibility Statistical Report

## Stationary Background Noise Experiment

### General Linear Model

**Notes**

| | | |
|---|---|---|
| Output Created | | 13-DEC-2018 09:15:54 |
| Comments | | |
| Input | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 20 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing. |
| | Cases Used | Statistics are based on all cases with valid data for all variables in the model. |

| | | |
|---|---|---|
| Syntax | | GLM up_4 up_0 up_3 up_6 dichotic_4 dichotic_0 dichotic_3 dichotic_6 MHA_4 MHA_0 MHA_3 MHA_6<br>MHAdichotic_4 MHAdichotic_0 MHAdichotic_3 MHAdichotic_6 BY Group<br>/WSFACTOR=processing 4 Polynomial SNR 4 Polynomial<br>/METHOD=SSTYPE(3)<br>/EMMEANS=TABLES(OVERALL)<br>/EMMEANS=TABLES(Group) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(processing) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(SNR) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(Group*processing) COMPARE(processing)ADJ(BONFERRONI)<br>/EMMEANS=TABLES(Group*SNR)<br>/EMMEANS=TABLES(Group*processing*SNR) COMPARE(processing)ADJ(BONFERRONI)<br>/CRITERIA=ALPHA(.05)<br>/WSDESIGN=processing SNR processing*SNR<br>/DESIGN=Group. |
| Resources | Processor Time | 00:00:00.09 |
| | Elapsed Time | 00:00:00.10 |

[DataSet1]

**Within-Subjects Factors**

Measure: MEASURE_1

| processing | SNR | Dependent Variable |
|---|---|---|
| 1 | 1 | up_4 |
| | 2 | up_0 |
| | 3 | up_3 |
| | 4 | up_6 |
| 2 | 1 | dichotic_4 |
| | 2 | dichotic_0 |
| | 3 | dichotic_3 |
| | 4 | dichotic_6 |
| 3 | 1 | MHA_4 |
| | 2 | MHA_0 |
| | 3 | MHA_3 |
| | 4 | MHA_6 |
| 4 | 1 | MHAdichotic_4 |
| | 2 | MHAdichotic_0 |
| | 3 | MHAdichotic_3 |
| | 4 | MHAdichotic_6 |

**Between-Subjects Factors**

| | | N |
|---|---|---|
| Group | HI | 10 |
| | NH | 10 |

**Multivariate Tests[a]**

| Effect | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| processing | Pillai's Trace | .600 | 7.992[b] | 3.000 | 16.000 | .002 |
| | Wilks' Lambda | .400 | 7.992[b] | 3.000 | 16.000 | .002 |
| | Hotelling's Trace | 1.498 | 7.992[b] | 3.000 | 16.000 | .002 |
| | Roy's Largest Root | 1.498 | 7.992[b] | 3.000 | 16.000 | .002 |
| processing * Group | Pillai's Trace | .595 | 7.822[b] | 3.000 | 16.000 | .002 |
| | Wilks' Lambda | .405 | 7.822[b] | 3.000 | 16.000 | .002 |
| | Hotelling's Trace | 1.467 | 7.822[b] | 3.000 | 16.000 | .002 |
| | Roy's Largest Root | 1.467 | 7.822[b] | 3.000 | 16.000 | .002 |
| SNR | Pillai's Trace | .977 | 222.484[b] | 3.000 | 16.000 | .000 |
| | Wilks' Lambda | .023 | 222.484[b] | 3.000 | 16.000 | .000 |
| | Hotelling's Trace | 41.716 | 222.484[b] | 3.000 | 16.000 | .000 |
| | Roy's Largest Root | 41.716 | 222.484[b] | 3.000 | 16.000 | .000 |
| SNR * Group | Pillai's Trace | .186 | 1.216[b] | 3.000 | 16.000 | .336 |
| | Wilks' Lambda | .814 | 1.216[b] | 3.000 | 16.000 | .336 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Hotelling's Trace | .228 | 1.216[b] | 3.000 | 16.000 | .336 |
| | Roy's Largest Root | .228 | 1.216[b] | 3.000 | 16.000 | .336 |
| processing * SNR | Pillai's Trace | .868 | 7.283[b] | 9.000 | 10.000 | .002 |
| | Wilks' Lambda | .132 | 7.283[b] | 9.000 | 10.000 | .002 |
| | Hotelling's Trace | 6.555 | 7.283[b] | 9.000 | 10.000 | .002 |
| | Roy's Largest Root | 6.555 | 7.283[b] | 9.000 | 10.000 | .002 |
| processing * SNR * Group | Pillai's Trace | .567 | 1.456[b] | 9.000 | 10.000 | .283 |
| | Wilks' Lambda | .433 | 1.456[b] | 9.000 | 10.000 | .283 |
| | Hotelling's Trace | 1.310 | 1.456[b] | 9.000 | 10.000 | .283 |
| | Roy's Largest Root | 1.310 | 1.456[b] | 9.000 | 10.000 | .283 |

a. Design: Intercept + Group

Within Subjects Design: processing + SNR + processing * SNR

b. Exact statistic

**Mauchly's Test of Sphericity[a]**

Measure: MEASURE_1

| | | | | | Epsilon[b] | | |
|---|---|---|---|---|---|---|---|
| Within Subjects Effect | Mauchly's W | Approx. Chi-Square | df | Sig. | Greenhouse-Geisser | Huynh-Feldt | Lower-bound |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| processing | .882 | 2.098 | 5 | .836 | .928 | 1.000 | .333 |
| SNR | .302 | 20.035 | 5 | .001 | .643 | .758 | .333 |
| processing * SNR | .072 | 38.920 | 44 | .720 | .667 | 1.000 | .111 |

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + Group

Within Subjects Design: processing + SNR + processing * SNR

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

**Tests of Within-Subjects Effects**

Measure: MEASURE_1

| Source | | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| processing | Sphericity Assumed | 2459.065 | 3 | 819.688 | 9.121 | .000 |
| | Greenhouse-Geisser | 2459.065 | 2.784 | 883.160 | 9.121 | .000 |
| | Huynh-Feldt | 2459.065 | 3.000 | 819.688 | 9.121 | .000 |
| | Lower-bound | 2459.065 | 1.000 | 2459.065 | 9.121 | .007 |
| processing * Group | Sphericity Assumed | 2259.666 | 3 | 753.222 | 8.381 | .000 |
| | Greenhouse-Geisser | 2259.666 | 2.784 | 811.547 | 8.381 | .000 |
| | Huynh-Feldt | 2259.666 | 3.000 | 753.222 | 8.381 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Lower-bound | 2259.666 | 1.000 | 2259.666 | 8.381 | .010 |
| Error(processing) | Sphericity Assumed | 4852.974 | 54 | 89.870 | | |
| | Greenhouse-Geisser | 4852.974 | 50.119 | 96.829 | | |
| | Huynh-Feldt | 4852.974 | 54.000 | 89.870 | | |
| | Lower-bound | 4852.974 | 18.000 | 269.610 | | |
| SNR | Sphericity Assumed | 269928.715 | 3 | 89976.238 | 348.182 | .000 |
| | Greenhouse-Geisser | 269928.715 | 1.928 | 140005.524 | 348.182 | .000 |
| | Huynh-Feldt | 269928.715 | 2.275 | 118663.316 | 348.182 | .000 |
| | Lower-bound | 269928.715 | 1.000 | 269928.715 | 348.182 | .000 |
| SNR * Group | Sphericity Assumed | 664.002 | 3 | 221.334 | .856 | .469 |
| | Greenhouse-Geisser | 664.002 | 1.928 | 344.402 | .856 | .430 |
| | Huynh-Feldt | 664.002 | 2.275 | 291.902 | .856 | .445 |
| | Lower-bound | 664.002 | 1.000 | 664.002 | .856 | .367 |
| Error(SNR) | Sphericity Assumed | 13954.530 | 54 | 258.417 | | |
| | Greenhouse-Geisser | 13954.530 | 34.704 | 402.104 | | |
| | Huynh-Feldt | 13954.530 | 40.945 | 340.808 | | |
| | Lower-bound | 13954.530 | 18.000 | 775.252 | | |
| processing * SNR | Sphericity Assumed | 6422.901 | 9 | 713.656 | 6.640 | .000 |
| | Greenhouse-Geisser | 6422.901 | 6.005 | 1069.567 | 6.640 | .000 |
| | Huynh-Feldt | 6422.901 | 9.000 | 713.656 | 6.640 | .000 |
| | Lower-bound | 6422.901 | 1.000 | 6422.901 | 6.640 | .019 |

| | | | | | | |
|---|---|---|---|---|---|---|
| processing * SNR * Group | Sphericity Assumed | 1333.089 | 9 | 148.121 | 1.378 | .202 |
| | Greenhouse-Geisser | 1333.089 | 6.005 | 221.991 | 1.378 | .230 |
| | Huynh-Feldt | 1333.089 | 9.000 | 148.121 | 1.378 | .202 |
| | Lower-bound | 1333.089 | 1.000 | 1333.089 | 1.378 | .256 |
| Error(processing*SNR) | Sphericity Assumed | 17411.113 | 162 | 107.476 | | |
| | Greenhouse-Geisser | 17411.113 | 108.093 | 161.076 | | |
| | Huynh-Feldt | 17411.113 | 162.000 | 107.476 | | |
| | Lower-bound | 17411.113 | 18.000 | 967.284 | | |

**Tests of Within-Subjects Contrasts**

Measure: MEASURE_1

| Source | processing | SNR | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| processing | Linear | | 146.002 | 1 | 146.002 | 1.250 | .278 |
| | Quadratic | | 1609.376 | 1 | 1609.376 | 18.596 | .000 |
| | Cubic | | 703.686 | 1 | 703.686 | 10.626 | .004 |
| processing * Group | Linear | | 1696.007 | 1 | 1696.007 | 14.515 | .001 |
| | Quadratic | | 405.936 | 1 | 405.936 | 4.691 | .044 |
| | Cubic | | 157.723 | 1 | 157.723 | 2.382 | .140 |
| Error(processing) | Linear | | 2103.178 | 18 | 116.843 | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Quadratic | | 1557.767 | 18 | 86.543 | | |
| | Cubic | | 1192.028 | 18 | 66.224 | | |
| SNR | | Linear | 255359.686 | 1 | 255359.686 | 558.142 | .000 |
| | | Quadratic | 13501.785 | 1 | 13501.785 | 62.181 | .000 |
| | | Cubic | 1067.245 | 1 | 1067.245 | 10.609 | .004 |
| SNR * Group | | Linear | 350.621 | 1 | 350.621 | .766 | .393 |
| | | Quadratic | 202.957 | 1 | 202.957 | .935 | .346 |
| | | Cubic | 110.425 | 1 | 110.425 | 1.098 | .309 |
| Error(SNR) | | Linear | 8235.309 | 18 | 457.517 | | |
| | | Quadratic | 3908.448 | 18 | 217.136 | | |
| | | Cubic | 1810.772 | 18 | 100.598 | | |
| processing * SNR | Linear | Linear | 2230.780 | 1 | 2230.780 | 17.122 | .001 |
| | | Quadratic | 142.839 | 1 | 142.839 | 1.721 | .206 |
| | | Cubic | 310.707 | 1 | 310.707 | 4.626 | .045 |
| | Quadratic | Linear | 2185.130 | 1 | 2185.130 | 16.939 | .001 |
| | | Quadratic | 6.271 | 1 | 6.271 | .047 | .831 |
| | | Cubic | 99.469 | 1 | 99.469 | .732 | .403 |
| | Cubic | Linear | 30.602 | 1 | 30.602 | .362 | .555 |
| | | Quadratic | 4.437 | 1 | 4.437 | .039 | .846 |
| | | Cubic | 1412.667 | 1 | 1412.667 | 15.828 | .001 |
| processing * SNR * Group | Linear | Linear | 285.036 | 1 | 285.036 | 2.188 | .156 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Quadratic | 457.345 | 1 | 457.345 | 5.510 | .031 |
| | | Cubic | 41.663 | 1 | 41.663 | .620 | .441 |
| | Quadratic | Linear | 4.292 | 1 | 4.292 | .033 | .857 |
| | | Quadratic | 21.856 | 1 | 21.856 | .163 | .691 |
| | | Cubic | 3.447 | 1 | 3.447 | .025 | .875 |
| | Cubic | Linear | 12.718 | 1 | 12.718 | .151 | .703 |
| | | Quadratic | 499.607 | 1 | 499.607 | 4.368 | .051 |
| | | Cubic | 7.126 | 1 | 7.126 | .080 | .781 |
| Error(processing*SNR) | Linear | Linear | 2345.204 | 18 | 130.289 | | |
| | | Quadratic | 1493.991 | 18 | 83.000 | | |
| | | Cubic | 1208.969 | 18 | 67.165 | | |
| | Quadratic | Linear | 2322.033 | 18 | 129.002 | | |
| | | Quadratic | 2409.113 | 18 | 133.840 | | |
| | | Cubic | 2445.694 | 18 | 135.872 | | |
| | Cubic | Linear | 1520.839 | 18 | 84.491 | | |
| | | Quadratic | 2058.742 | 18 | 114.375 | | |
| | | Cubic | 1606.527 | 18 | 89.251 | | |

**Tests of Between-Subjects Effects**

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Intercept | 1694019.809 | 1 | 1694019.809 | 750.389 | .000 |
| Group | 27926.466 | 1 | 27926.466 | 12.370 | .002 |
| Error | 40635.385 | 18 | 2257.521 | | |

## Estimated Marginal Means

**1. Grand Mean**

Measure: MEASURE_1

| | | 95% Confidence Interval | |
|---|---|---|---|
| Mean | Std. Error | Lower Bound | Upper Bound |
| 72.759 | 2.656 | 67.178 | 78.339 |

## 2. Group

**Estimates**

Measure: MEASURE_1

| | | | 95% Confidence Interval | |
|---|---|---|---|---|
| Group | Mean | Std. Error | Lower Bound | Upper Bound |
| HI | 63.417 | 3.756 | 55.525 | 71.308 |
| NH | 82.100 | 3.756 | 74.209 | 89.992 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) Group | (J) Group | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| HI | NH | -18.684* | 5.312 | .002 | -29.844 | -7.523 |
| NH | HI | 18.684* | 5.312 | .002 | 7.523 | 29.844 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Univariate Tests**

Measure: MEASURE_1

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 1745.404 | 1 | 1745.404 | 12.370 | .002 |
| Error | 2539.712 | 18 | 141.095 | | |

The F tests the effect of Group. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

## 3. processing

**Estimates**

Measure: MEASURE_1

| processing | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| 1 | 68.947 | 2.870 | 62.916 | 74.977 |
| 2 | 76.689 | 2.942 | 70.508 | 82.869 |
| 3 | 73.314 | 2.762 | 67.512 | 79.116 |
| 4 | 72.085 | 2.659 | 66.499 | 77.671 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| 1 | 2 | -7.742* | 1.510 | .000 | -12.216 | -3.269 |
| | 3 | -4.367* | 1.414 | .038 | -8.555 | -.179 |
| | 4 | -3.139 | 1.707 | .495 | -8.195 | 1.918 |
| 2 | 1 | 7.742* | 1.510 | .000 | 3.269 | 12.216 |
| | 3 | 3.375 | 1.290 | .105 | -.447 | 7.196 |
| | 4 | 4.603 | 1.636 | .069 | -.243 | 9.449 |
| 3 | 1 | 4.367* | 1.414 | .038 | .179 | 8.555 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 2 | -3.375 | 1.290 | .105 | -7.196 | .447 |
| | 4 | 1.228 | 1.396 | 1.000 | -2.909 | 5.366 |
| 4 | 1 | 3.139 | 1.707 | .495 | -1.918 | 8.195 |
| | 2 | -4.603 | 1.636 | .069 | -9.449 | .243 |
| | 3 | -1.228 | 1.396 | 1.000 | -5.366 | 2.909 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .600 | 7.992[a] | 3.000 | 16.000 | .002 |
| Wilks' lambda | .400 | 7.992[a] | 3.000 | 16.000 | .002 |
| Hotelling's trace | 1.498 | 7.992[a] | 3.000 | 16.000 | .002 |
| Roy's largest root | 1.498 | 7.992[a] | 3.000 | 16.000 | .002 |

Each F tests the multivariate effect of processing. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 4. SNR

**Estimates**

Measure: MEASURE_1

| SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| 1 | 103.346 | 2.543 | 98.004 | 108.688 |
| 2 | 94.338 | 2.366 | 89.368 | 99.308 |
| 3 | 64.171 | 3.662 | 56.477 | 71.864 |
| 4 | 29.180 | 3.527 | 21.770 | 36.589 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) SNR | (J) SNR | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| 1 | 2 | 9.008* | 1.645 | .000 | 4.134 | 13.883 |
| | 3 | 39.175* | 3.299 | .000 | 29.401 | 48.950 |
| | 4 | 74.166* | 2.969 | .000 | 65.369 | 82.964 |
| 2 | 1 | -9.008* | 1.645 | .000 | -13.883 | -4.134 |
| | 3 | 30.167* | 2.266 | .000 | 23.453 | 36.881 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 4 | 65.158* | 2.550 | .000 | 57.603 | 72.713 |
| 3 | 1 | -39.175* | 3.299 | .000 | -48.950 | -29.401 |
| | 2 | -30.167* | 2.266 | .000 | -36.881 | -23.453 |
| | 4 | 34.991* | 2.172 | .000 | 28.557 | 41.425 |
| 4 | 1 | -74.166* | 2.969 | .000 | -82.964 | -65.369 |
| | 2 | -65.158* | 2.550 | .000 | -72.713 | -57.603 |
| | 3 | -34.991* | 2.172 | .000 | -41.425 | -28.557 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .977 | 222.484[a] | 3.000 | 16.000 | .000 |
| Wilks' lambda | .023 | 222.484[a] | 3.000 | 16.000 | .000 |
| Hotelling's trace | 41.716 | 222.484[a] | 3.000 | 16.000 | .000 |
| Roy's largest root | 41.716 | 222.484[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate effect of SNR. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 5. Group * processing

**Estimates**

Measure: MEASURE_1

| Group | processing | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|
| HI | 1 | 63.506 | 4.059 | 54.977 | 72.034 |
| | 2 | 68.192 | 4.160 | 59.452 | 76.932 |
| | 3 | 60.874 | 3.906 | 52.669 | 69.080 |
| | 4 | 61.095 | 3.760 | 53.195 | 68.995 |
| NH | 1 | 74.387 | 4.059 | 65.859 | 82.916 |
| | 2 | 85.185 | 4.160 | 76.445 | 93.925 |
| | 3 | 85.753 | 3.906 | 77.548 | 93.959 |
| | 4 | 83.076 | 3.760 | 75.176 | 90.976 |

**Pairwise Comparisons**

Measure: MEASURE_1

| Group | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | 95% Confidence Interval for Difference[b] Upper Bound |
|---|---|---|---|---|---|---|---|
| HI | 1 | 2 | -4.686 | 2.135 | .249 | -11.013 | 1.640 |
| | | 3 | 2.632 | 1.999 | 1.000 | -3.291 | 8.555 |
| | | 4 | 2.411 | 2.414 | 1.000 | -4.740 | 9.562 |
| | 2 | 1 | 4.686 | 2.135 | .249 | -1.640 | 11.013 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 3 | 7.318* | 1.824 | .005 | 1.913 | 12.722 |
| | | 4 | 7.097* | 2.313 | .040 | .243 | 13.950 |
| | 3 | 1 | -2.632 | 1.999 | 1.000 | -8.555 | 3.291 |
| | | 2 | -7.318* | 1.824 | .005 | -12.722 | -1.913 |
| | | 4 | -.221 | 1.975 | 1.000 | -6.072 | 5.630 |
| | 4 | 1 | -2.411 | 2.414 | 1.000 | -9.562 | 4.740 |
| | | 2 | -7.097* | 2.313 | .040 | -13.950 | -.243 |
| | | 3 | .221 | 1.975 | 1.000 | -5.630 | 6.072 |
| NH | 1 | 2 | -10.798* | 2.135 | .000 | -17.124 | -4.471 |
| | | 3 | -11.366* | 1.999 | .000 | -17.289 | -5.443 |
| | | 4 | -8.688* | 2.414 | .012 | -15.839 | -1.537 |
| | 2 | 1 | 10.798* | 2.135 | .000 | 4.471 | 17.124 |
| | | 3 | -.568 | 1.824 | 1.000 | -5.973 | 4.836 |
| | | 4 | 2.110 | 2.313 | 1.000 | -4.744 | 8.963 |
| | 3 | 1 | 11.366* | 1.999 | .000 | 5.443 | 17.289 |
| | | 2 | .568 | 1.824 | 1.000 | -4.836 | 5.973 |
| | | 4 | 2.678 | 1.975 | 1.000 | -3.173 | 8.529 |
| | 4 | 1 | 8.688* | 2.414 | .012 | 1.537 | 15.839 |
| | | 2 | -2.110 | 2.313 | 1.000 | -8.963 | 4.744 |
| | | 3 | -2.678 | 1.975 | 1.000 | -8.529 | 3.173 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| Group | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| HI | Pillai's trace | .486 | 5.046[a] | 3.000 | 16.000 | .012 |
| | Wilks' lambda | .514 | 5.046[a] | 3.000 | 16.000 | .012 |
| | Hotelling's trace | .946 | 5.046[a] | 3.000 | 16.000 | .012 |
| | Roy's largest root | .946 | 5.046[a] | 3.000 | 16.000 | .012 |
| NH | Pillai's trace | .669 | 10.768[a] | 3.000 | 16.000 | .000 |
| | Wilks' lambda | .331 | 10.768[a] | 3.000 | 16.000 | .000 |
| | Hotelling's trace | 2.019 | 10.768[a] | 3.000 | 16.000 | .000 |
| | Roy's largest root | 2.019 | 10.768[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

**6. Group * SNR**

Measure: MEASURE_1

| Group | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| HI | 1 | 93.134 | 3.596 | 85.578 | 100.689 |
| | 2 | 84.519 | 3.346 | 77.491 | 91.548 |
| | 3 | 53.713 | 5.179 | 42.832 | 64.593 |
| | 4 | 22.301 | 4.988 | 11.823 | 32.780 |
| NH | 1 | 113.559 | 3.596 | 106.004 | 121.114 |
| | 2 | 104.156 | 3.346 | 97.127 | 111.185 |
| | 3 | 74.629 | 5.179 | 63.749 | 85.509 |
| | 4 | 36.058 | 4.988 | 25.580 | 46.537 |

# 7. Group * processing * SNR

**Estimates**

Measure: MEASURE_1

| Group | processing | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| HI | 1 | 1 | 106.104 | 4.467 | 96.720 | 115.489 |
| | | 2 | 83.864 | 4.584 | 74.235 | 93.494 |
| | | 3 | 49.335 | 5.815 | 37.118 | 61.552 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 14.719 | 5.857 | 2.413 | 27.024 |
| | 2 | 1 | 96.279 | 3.783 | 88.331 | 104.227 |
| | | 2 | 91.631 | 4.107 | 83.002 | 100.260 |
| | | 3 | 56.718 | 6.689 | 42.666 | 70.771 |
| | | 4 | 28.139 | 6.286 | 14.932 | 41.346 |
| | 3 | 1 | 86.292 | 4.710 | 76.397 | 96.187 |
| | | 2 | 74.622 | 4.849 | 64.434 | 84.810 |
| | | 3 | 56.352 | 4.762 | 46.347 | 66.357 |
| | | 4 | 26.230 | 5.741 | 14.169 | 38.292 |
| | 4 | 1 | 83.858 | 3.888 | 75.690 | 92.027 |
| | | 2 | 87.960 | 3.749 | 80.083 | 95.837 |
| | | 3 | 52.444 | 6.110 | 39.608 | 65.280 |
| | | 4 | 20.118 | 5.883 | 7.758 | 32.477 |
| NH | 1 | 1 | 112.041 | 4.467 | 102.657 | 121.425 |
| | | 2 | 96.589 | 4.584 | 86.959 | 106.218 |
| | | 3 | 69.165 | 5.815 | 56.949 | 81.382 |
| | | 4 | 19.754 | 5.857 | 7.449 | 32.060 |
| | 2 | 1 | 115.108 | 3.783 | 107.160 | 123.056 |
| | | 2 | 107.686 | 4.107 | 99.057 | 116.315 |
| | | 3 | 74.314 | 6.689 | 60.262 | 88.367 |
| | | 4 | 43.633 | 6.286 | 30.426 | 56.840 |

| | | | | | |
|---|---|---|---|---|---|
| 3 | 1 | 112.209 | 4.710 | 102.314 | 122.105 |
| | 2 | 104.155 | 4.849 | 93.967 | 114.343 |
| | 3 | 85.376 | 4.762 | 75.370 | 95.381 |
| | 4 | 41.274 | 5.741 | 29.212 | 53.335 |
| 4 | 1 | 114.876 | 3.888 | 106.708 | 123.045 |
| | 2 | 108.194 | 3.749 | 100.317 | 116.071 |
| | 3 | 69.661 | 6.110 | 56.825 | 82.497 |
| | 4 | 39.572 | 5.883 | 27.212 | 51.931 |

**Pairwise Comparisons**

Measure: MEASURE_1

| | | | | | | | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|---|
| Group | SNR | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | Lower Bound | Upper Bound |
| HI | 1 | 1 | 2 | 9.825* | 2.456 | .005 | 2.550 | 17.100 |
| | | | 3 | 19.812* | 4.021 | .001 | 7.899 | 31.726 |
| | | | 4 | 22.246* | 4.242 | .000 | 9.678 | 34.814 |
| | | 2 | 1 | -9.825* | 2.456 | .005 | -17.100 | -2.550 |
| | | | 3 | 9.987* | 3.319 | .045 | .153 | 19.821 |
| | | | 4 | 12.421* | 3.740 | .023 | 1.339 | 23.502 |
| | | 3 | 1 | -19.812* | 4.021 | .001 | -31.726 | -7.899 |
| | | | 2 | -9.987* | 3.319 | .045 | -19.821 | -.153 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 4 | 2.434 | 3.761 | 1.000 | -8.709 | 13.576 |
| | 4 | 1 | -22.246* | 4.242 | .000 | -34.814 | -9.678 |
| | | 2 | -12.421* | 3.740 | .023 | -23.502 | -1.339 |
| | | 3 | -2.434 | 3.761 | 1.000 | -13.576 | 8.709 |
| 2 | 1 | 2 | -7.767 | 5.149 | .893 | -23.023 | 7.490 |
| | | 3 | 9.242 | 4.866 | .442 | -5.175 | 23.660 |
| | | 4 | -4.095 | 4.033 | 1.000 | -16.044 | 7.853 |
| | 2 | 1 | 7.767 | 5.149 | .893 | -7.490 | 23.023 |
| | | 3 | 17.009* | 3.668 | .001 | 6.141 | 27.877 |
| | | 4 | 3.671 | 3.967 | 1.000 | -8.081 | 15.423 |
| | 3 | 1 | -9.242 | 4.866 | .442 | -23.660 | 5.175 |
| | | 2 | -17.009* | 3.668 | .001 | -27.877 | -6.141 |
| | | 4 | -13.338 | 5.203 | .117 | -28.751 | 2.076 |
| | 4 | 1 | 4.095 | 4.033 | 1.000 | -7.853 | 16.044 |
| | | 2 | -3.671 | 3.967 | 1.000 | -15.423 | 8.081 |
| | | 3 | 13.338 | 5.203 | .117 | -2.076 | 28.751 |
| 3 | 1 | 2 | -7.383 | 4.804 | .850 | -21.617 | 6.851 |
| | | 3 | -7.017 | 3.651 | .423 | -17.832 | 3.799 |
| | | 4 | -3.109 | 4.309 | 1.000 | -15.875 | 9.657 |
| | 2 | 1 | 7.383 | 4.804 | .850 | -6.851 | 21.617 |
| | | 3 | .367 | 4.898 | 1.000 | -14.146 | 14.879 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | 4 | 4.274 | 5.201 | 1.000 | -11.136 | 19.684 |
| | | 3 | 1 | 7.017 | 3.651 | .423 | -3.799 | 17.832 |
| | | | 2 | -.367 | 4.898 | 1.000 | -14.879 | 14.146 |
| | | | 4 | 3.907 | 4.372 | 1.000 | -9.045 | 16.860 |
| | | 4 | 1 | 3.109 | 4.309 | 1.000 | -9.657 | 15.875 |
| | | | 2 | -4.274 | 5.201 | 1.000 | -19.684 | 11.136 |
| | | | 3 | -3.907 | 4.372 | 1.000 | -16.860 | 9.045 |
| | 4 | 1 | 2 | -13.420* | 3.576 | .009 | -24.015 | -2.825 |
| | | | 3 | -11.512 | 5.684 | .347 | -28.350 | 5.327 |
| | | | 4 | -5.399 | 4.880 | 1.000 | -19.858 | 9.059 |
| | | 2 | 1 | 13.420* | 3.576 | .009 | 2.825 | 24.015 |
| | | | 3 | 1.908 | 5.022 | 1.000 | -12.970 | 16.787 |
| | | | 4 | 8.021 | 5.929 | 1.000 | -9.544 | 25.586 |
| | | 3 | 1 | 11.512 | 5.684 | .347 | -5.327 | 28.350 |
| | | | 2 | -1.908 | 5.022 | 1.000 | -16.787 | 12.970 |
| | | | 4 | 6.113 | 6.188 | 1.000 | -12.220 | 24.445 |
| | | 4 | 1 | 5.399 | 4.880 | 1.000 | -9.059 | 19.858 |
| | | | 2 | -8.021 | 5.929 | 1.000 | -25.586 | 9.544 |
| | | | 3 | -6.113 | 6.188 | 1.000 | -24.445 | 12.220 |
| NH | 1 | 1 | 2 | -3.067 | 2.456 | 1.000 | -10.342 | 4.208 |
| | | | 3 | -.168 | 4.021 | 1.000 | -12.082 | 11.745 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 4 | -2.835 | 4.242 | 1.000 | -15.404 | 9.733 |
| | 2 | 1 | 3.067 | 2.456 | 1.000 | -4.208 | 10.342 |
| | | 3 | 2.898 | 3.319 | 1.000 | -6.936 | 12.733 |
| | | 4 | .232 | 3.740 | 1.000 | -10.850 | 11.313 |
| | 3 | 1 | .168 | 4.021 | 1.000 | -11.745 | 12.082 |
| | | 2 | -2.898 | 3.319 | 1.000 | -12.733 | 6.936 |
| | | 4 | -2.667 | 3.761 | 1.000 | -13.809 | 8.475 |
| | 4 | 1 | 2.835 | 4.242 | 1.000 | -9.733 | 15.404 |
| | | 2 | -.232 | 3.740 | 1.000 | -11.313 | 10.850 |
| | | 3 | 2.667 | 3.761 | 1.000 | -8.475 | 13.809 |
| 2 | 1 | 2 | -11.097 | 5.149 | .270 | -26.354 | 4.159 |
| | | 3 | -7.566 | 4.866 | .824 | -21.984 | 6.851 |
| | | 4 | -11.605 | 4.033 | .060 | -23.553 | .343 |
| | 2 | 1 | 11.097 | 5.149 | .270 | -4.159 | 26.354 |
| | | 3 | 3.531 | 3.668 | 1.000 | -7.336 | 14.399 |
| | | 4 | -.508 | 3.967 | 1.000 | -12.260 | 11.244 |
| | 3 | 1 | 7.566 | 4.866 | .824 | -6.851 | 21.984 |
| | | 2 | -3.531 | 3.668 | 1.000 | -14.399 | 7.336 |
| | | 4 | -4.039 | 5.203 | 1.000 | -19.452 | 11.375 |
| | 4 | 1 | 11.605 | 4.033 | .060 | -.343 | 23.553 |
| | | 2 | .508 | 3.967 | 1.000 | -11.244 | 12.260 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 3 | 4.039 | 5.203 | 1.000 | -11.375 | 19.452 |
| 3 | 1 | 2 | -5.149 | 4.804 | 1.000 | -19.383 | 9.085 |
| | | 3 | -16.210* | 3.651 | .002 | -27.026 | -5.394 |
| | | 4 | -.495 | 4.309 | 1.000 | -13.262 | 12.271 |
| | 2 | 1 | 5.149 | 4.804 | 1.000 | -9.085 | 19.383 |
| | | 3 | -11.061 | 4.898 | .220 | -25.574 | 3.451 |
| | | 4 | 4.653 | 5.201 | 1.000 | -10.756 | 20.063 |
| | 3 | 1 | 16.210* | 3.651 | .002 | 5.394 | 27.026 |
| | | 2 | 11.061 | 4.898 | .220 | -3.451 | 25.574 |
| | | 4 | 15.715* | 4.372 | .012 | 2.762 | 28.667 |
| | 4 | 1 | .495 | 4.309 | 1.000 | -12.271 | 13.262 |
| | | 2 | -4.653 | 5.201 | 1.000 | -20.063 | 10.756 |
| | | 3 | -15.715* | 4.372 | .012 | -28.667 | -2.762 |
| 4 | 1 | 2 | -23.879* | 3.576 | .000 | -34.473 | -13.284 |
| | | 3 | -21.519* | 5.684 | .008 | -38.358 | -4.681 |
| | | 4 | -19.817* | 4.880 | .004 | -34.276 | -5.359 |
| | 2 | 1 | 23.879* | 3.576 | .000 | 13.284 | 34.473 |
| | | 3 | 2.360 | 5.022 | 1.000 | -12.519 | 17.238 |
| | | 4 | 4.061 | 5.929 | 1.000 | -13.504 | 21.626 |
| | 3 | 1 | 21.519* | 5.684 | .008 | 4.681 | 38.358 |
| | | 2 | -2.360 | 5.022 | 1.000 | -17.238 | 12.519 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | 4 | 1.702 | 6.188 | 1.000 | -16.631 | 20.034 |
| | 4 | 1 | 19.817* | 4.880 | .004 | 5.359 | 34.276 |
| | | 2 | -4.061 | 5.929 | 1.000 | -21.626 | 13.504 |
| | | 3 | -1.702 | 6.188 | 1.000 | -20.034 | 16.631 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| Group | SNR | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|---|
| HI | 1 | Pillai's trace | .650 | 9.903[a] | 3.000 | 16.000 | .001 |
| | | Wilks' lambda | .350 | 9.903[a] | 3.000 | 16.000 | .001 |
| | | Hotelling's trace | 1.857 | 9.903[a] | 3.000 | 16.000 | .001 |
| | | Roy's largest root | 1.857 | 9.903[a] | 3.000 | 16.000 | .001 |
| | 2 | Pillai's trace | .566 | 6.951[a] | 3.000 | 16.000 | .003 |
| | | Wilks' lambda | .434 | 6.951[a] | 3.000 | 16.000 | .003 |
| | | Hotelling's trace | 1.303 | 6.951[a] | 3.000 | 16.000 | .003 |
| | | Roy's largest root | 1.303 | 6.951[a] | 3.000 | 16.000 | .003 |
| | 3 | Pillai's trace | .204 | 1.369[a] | 3.000 | 16.000 | .288 |
| | | Wilks' lambda | .796 | 1.369[a] | 3.000 | 16.000 | .288 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Hotelling's trace | .257 | 1.369[a] | 3.000 | 16.000 | .288 |
| | | Roy's largest root | .257 | 1.369[a] | 3.000 | 16.000 | .288 |
| | 4 | Pillai's trace | .455 | 4.445[a] | 3.000 | 16.000 | .019 |
| | | Wilks' lambda | .545 | 4.445[a] | 3.000 | 16.000 | .019 |
| | | Hotelling's trace | .833 | 4.445[a] | 3.000 | 16.000 | .019 |
| | | Roy's largest root | .833 | 4.445[a] | 3.000 | 16.000 | .019 |
| NH | 1 | Pillai's trace | .119 | .722[a] | 3.000 | 16.000 | .553 |
| | | Wilks' lambda | .881 | .722[a] | 3.000 | 16.000 | .553 |
| | | Hotelling's trace | .135 | .722[a] | 3.000 | 16.000 | .553 |
| | | Roy's largest root | .135 | .722[a] | 3.000 | 16.000 | .553 |
| | 2 | Pillai's trace | .326 | 2.583[a] | 3.000 | 16.000 | .089 |
| | | Wilks' lambda | .674 | 2.583[a] | 3.000 | 16.000 | .089 |
| | | Hotelling's trace | .484 | 2.583[a] | 3.000 | 16.000 | .089 |
| | | Roy's largest root | .484 | 2.583[a] | 3.000 | 16.000 | .089 |
| | 3 | Pillai's trace | .562 | 6.856[a] | 3.000 | 16.000 | .004 |
| | | Wilks' lambda | .438 | 6.856[a] | 3.000 | 16.000 | .004 |
| | | Hotelling's trace | 1.286 | 6.856[a] | 3.000 | 16.000 | .004 |
| | | Roy's largest root | 1.286 | 6.856[a] | 3.000 | 16.000 | .004 |
| | 4 | Pillai's trace | .768 | 17.628[a] | 3.000 | 16.000 | .000 |
| | | Wilks' lambda | .232 | 17.628[a] | 3.000 | 16.000 | .000 |
| | | Hotelling's trace | 3.305 | 17.628[a] | 3.000 | 16.000 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Roy's largest root | 3.305 | 17.628[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## Non-stationary Background Noise Experiment

## General Linear Model

**Notes**

| | | |
|---|---|---|
| Output Created | | 13-DEC-2018 09:27:37 |
| Comments | | |
| Input | Active Dataset | DataSet1 |
| | Filter | <none> |
| | Weight | <none> |
| | Split File | <none> |
| | N of Rows in Working Data File | 20 |
| Missing Value Handling | Definition of Missing | User-defined missing values are treated as missing. |
| | Cases Used | Statistics are based on all cases with valid data for all variables in the model. |

| | | |
|---|---|---|
| Syntax | | GLM up_4 up_0 up_3 up_6 dichotic_4 dichotic_0 dichotic_3 dichotic_6 MHA_4 MHA_0 MHA_3 MHA_6<br>MHAdichotic_4 MHAdichotic_0 MHAdichotic_3 MHAdichotic_6 BY Group<br>/WSFACTOR=processing 4 Polynomial SNR 4 Polynomial<br>/METHOD=SSTYPE(3)<br>/EMMEANS=TABLES(OVERALL)<br>/EMMEANS=TABLES(Group) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(processing) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(SNR) COMPARE ADJ(BONFERRONI)<br>/EMMEANS=TABLES(Group*processing) COMPARE(processing)ADJ(BONFERRONI)<br>/EMMEANS=TABLES(Group*SNR)<br>/EMMEANS=TABLES(processing*SNR)<br>/EMMEANS=TABLES(Group*processing*SNR) COMPARE(processing)ADJ(BONFERRONI)<br>/CRITERIA=ALPHA(.05)<br>/WSDESIGN=processing SNR processing*SNR<br>/DESIGN=Group. |
| Resources | Processor Time | 00:00:00.05 |

| | |
|---|---|
| Elapsed Time | 00:00:00.09 |

[DataSet1]

**Within-Subjects Factors**

Measure: MEASURE_1

| processing | SNR | Dependent Variable |
|---|---|---|
| 1 | 1 | up_4 |
| | 2 | up_0 |
| | 3 | up_3 |
| | 4 | up_6 |
| 2 | 1 | dichotic_4 |
| | 2 | dichotic_0 |
| | 3 | dichotic_3 |
| | 4 | dichotic_6 |
| 3 | 1 | MHA_4 |
| | 2 | MHA_0 |
| | 3 | MHA_3 |
| | 4 | MHA_6 |
| 4 | 1 | MHAdichotic_4 |
| | 2 | MHAdichotic_0 |

| | |
|---|---|
| 3 | MHAdichotic_3 |
| 4 | MHAdichotic_6 |

**Between-Subjects Factors**

| | | N |
|---|---|---|
| Group | HIA | 10 |
| | NHA | 10 |

**Multivariate Tests[a]**

| Effect | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| processing | Pillai's Trace | .857 | 31.890[b] | 3.000 | 16.000 | .000 |
| | Wilks' Lambda | .143 | 31.890[b] | 3.000 | 16.000 | .000 |
| | Hotelling's Trace | 5.979 | 31.890[b] | 3.000 | 16.000 | .000 |
| | Roy's Largest Root | 5.979 | 31.890[b] | 3.000 | 16.000 | .000 |
| processing * Group | Pillai's Trace | .378 | 3.234[b] | 3.000 | 16.000 | .050 |
| | Wilks' Lambda | .622 | 3.234[b] | 3.000 | 16.000 | .050 |
| | Hotelling's Trace | .606 | 3.234[b] | 3.000 | 16.000 | .050 |
| | Roy's Largest Root | .606 | 3.234[b] | 3.000 | 16.000 | .050 |
| SNR | Pillai's Trace | .991 | 559.677[b] | 3.000 | 16.000 | .000 |
| | Wilks' Lambda | .009 | 559.677[b] | 3.000 | 16.000 | .000 |
| | Hotelling's Trace | 104.939 | 559.677[b] | 3.000 | 16.000 | .000 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Roy's Largest Root | 104.939 | 559.677[b] | 3.000 | 16.000 | .000 |
| SNR * Group | Pillai's Trace | .243 | 1.712[b] | 3.000 | 16.000 | .205 |
| | Wilks' Lambda | .757 | 1.712[b] | 3.000 | 16.000 | .205 |
| | Hotelling's Trace | .321 | 1.712[b] | 3.000 | 16.000 | .205 |
| | Roy's Largest Root | .321 | 1.712[b] | 3.000 | 16.000 | .205 |
| processing * SNR | Pillai's Trace | .853 | 6.452[b] | 9.000 | 10.000 | .004 |
| | Wilks' Lambda | .147 | 6.452[b] | 9.000 | 10.000 | .004 |
| | Hotelling's Trace | 5.807 | 6.452[b] | 9.000 | 10.000 | .004 |
| | Roy's Largest Root | 5.807 | 6.452[b] | 9.000 | 10.000 | .004 |
| processing * SNR * Group | Pillai's Trace | .702 | 2.615[b] | 9.000 | 10.000 | .075 |
| | Wilks' Lambda | .298 | 2.615[b] | 9.000 | 10.000 | .075 |
| | Hotelling's Trace | 2.354 | 2.615[b] | 9.000 | 10.000 | .075 |
| | Roy's Largest Root | 2.354 | 2.615[b] | 9.000 | 10.000 | .075 |

a. Design: Intercept + Group

Within Subjects Design: processing + SNR + processing * SNR

b. Exact statistic

**Mauchly's Test of Sphericity[a]**

Measure: MEASURE_1

| Within Subjects Effect | Mauchly's W | Approx. Chi-Square | df | Sig. | Epsilon[b] | | |
|---|---|---|---|---|---|---|---|
| | | | | | Greenhouse-Geisser | Huynh-Feldt | Lower-bound |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| processing | .692 | 6.167 | 5 | .291 | .842 | 1.000 | .333 |
| SNR | .490 | 11.944 | 5 | .036 | .768 | .935 | .333 |
| processing * SNR | .043 | 46.459 | 44 | .411 | .655 | 1.000 | .111 |

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept + Group

Within Subjects Design: processing + SNR + processing * SNR

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

**Tests of Within-Subjects Effects**

Measure: MEASURE_1

| Source | | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| processing | Sphericity Assumed | 6892.697 | 3 | 2297.566 | 17.754 | .000 |
| | Greenhouse-Geisser | 6892.697 | 2.525 | 2729.821 | 17.754 | .000 |
| | Huynh-Feldt | 6892.697 | 3.000 | 2297.566 | 17.754 | .000 |
| | Lower-bound | 6892.697 | 1.000 | 6892.697 | 17.754 | .001 |
| processing * Group | Sphericity Assumed | 1661.247 | 3 | 553.749 | 4.279 | .009 |
| | Greenhouse-Geisser | 1661.247 | 2.525 | 657.929 | 4.279 | .013 |
| | Huynh-Feldt | 1661.247 | 3.000 | 553.749 | 4.279 | .009 |
| | Lower-bound | 1661.247 | 1.000 | 1661.247 | 4.279 | .053 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Error(processing) | Sphericity Assumed | 6988.029 | 54 | 129.408 | | |
| | Greenhouse-Geisser | 6988.029 | 45.449 | 153.754 | | |
| | Huynh-Feldt | 6988.029 | 54.000 | 129.408 | | |
| | Lower-bound | 6988.029 | 18.000 | 388.224 | | |
| SNR | Sphericity Assumed | 263094.063 | 3 | 87698.021 | 698.107 | .000 |
| | Greenhouse-Geisser | 263094.063 | 2.303 | 114261.065 | 698.107 | .000 |
| | Huynh-Feldt | 263094.063 | 2.806 | 93751.874 | 698.107 | .000 |
| | Lower-bound | 263094.063 | 1.000 | 263094.063 | 698.107 | .000 |
| SNR * Group | Sphericity Assumed | 689.455 | 3 | 229.818 | 1.829 | .153 |
| | Greenhouse-Geisser | 689.455 | 2.303 | 299.428 | 1.829 | .168 |
| | Huynh-Feldt | 689.455 | 2.806 | 245.683 | 1.829 | .157 |
| | Lower-bound | 689.455 | 1.000 | 689.455 | 1.829 | .193 |
| Error(SNR) | Sphericity Assumed | 6783.623 | 54 | 125.623 | | |
| | Greenhouse-Geisser | 6783.623 | 41.446 | 163.673 | | |
| | Huynh-Feldt | 6783.623 | 50.513 | 134.294 | | |
| | Lower-bound | 6783.623 | 18.000 | 376.868 | | |
| processing * SNR | Sphericity Assumed | 8123.978 | 9 | 902.664 | 6.811 | .000 |
| | Greenhouse-Geisser | 8123.978 | 5.891 | 1378.976 | 6.811 | .000 |
| | Huynh-Feldt | 8123.978 | 9.000 | 902.664 | 6.811 | .000 |
| | Lower-bound | 8123.978 | 1.000 | 8123.978 | 6.811 | .018 |
| processing * SNR * Group | Sphericity Assumed | 2436.069 | 9 | 270.674 | 2.042 | .038 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | Greenhouse-Geisser | 2436.069 | 5.891 | 413.502 | 2.042 | .067 |
| | Huynh-Feldt | 2436.069 | 9.000 | 270.674 | 2.042 | .038 |
| | Lower-bound | 2436.069 | 1.000 | 2436.069 | 2.042 | .170 |
| Error(processing*SNR) | Sphericity Assumed | 21468.625 | 162 | 132.522 | | |
| | Greenhouse-Geisser | 21468.625 | 106.044 | 202.451 | | |
| | Huynh-Feldt | 21468.625 | 162.000 | 132.522 | | |
| | Lower-bound | 21468.625 | 18.000 | 1192.701 | | |

**Tests of Within-Subjects Contrasts**

Measure: MEASURE_1

| Source | processing | SNR | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| processing | Linear | | 3840.295 | 1 | 3840.295 | 59.269 | .000 |
| | Quadratic | | 22.969 | 1 | 22.969 | .160 | .694 |
| | Cubic | | 3029.433 | 1 | 3029.433 | 16.839 | .001 |
| processing * Group | Linear | | 108.019 | 1 | 108.019 | 1.667 | .213 |
| | Quadratic | | 881.676 | 1 | 881.676 | 6.143 | .023 |
| | Cubic | | 671.552 | 1 | 671.552 | 3.733 | .069 |
| Error(processing) | Linear | | 1166.303 | 18 | 64.795 | | |
| | Quadratic | | 2583.464 | 18 | 143.526 | | |
| | Cubic | | 3238.262 | 18 | 179.903 | | |
| SNR | | Linear | 263092.957 | 1 | 263092.957 | 1774.863 | .000 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Quadratic | .787 | 1 | .787 | .004 | .949 |
| | | Cubic | .319 | 1 | .319 | .007 | .932 |
| SNR * Group | | Linear | 412.042 | 1 | 412.042 | 2.780 | .113 |
| | | Quadratic | 203.581 | 1 | 203.581 | 1.096 | .309 |
| | | Cubic | 73.833 | 1 | 73.833 | 1.724 | .206 |
| Error(SNR) | | Linear | 2668.191 | 18 | 148.233 | | |
| | | Quadratic | 3344.730 | 18 | 185.818 | | |
| | | Cubic | 770.702 | 18 | 42.817 | | |
| processing * SNR | Linear | Linear | 211.686 | 1 | 211.686 | 1.622 | .219 |
| | | Quadratic | 57.987 | 1 | 57.987 | .728 | .405 |
| | | Cubic | 1458.297 | 1 | 1458.297 | 11.829 | .003 |
| | Quadratic | Linear | 463.040 | 1 | 463.040 | 3.784 | .068 |
| | | Quadratic | 117.421 | 1 | 117.421 | .617 | .442 |
| | | Cubic | 191.544 | 1 | 191.544 | 1.355 | .260 |
| | Cubic | Linear | 3708.596 | 1 | 3708.596 | 26.668 | .000 |
| | | Quadratic | 1904.731 | 1 | 1904.731 | 9.041 | .008 |
| | | Cubic | 10.676 | 1 | 10.676 | .192 | .666 |
| processing * SNR * Group | Linear | Linear | 969.021 | 1 | 969.021 | 7.426 | .014 |
| | | Quadratic | 5.365 | 1 | 5.365 | .067 | .798 |
| | | Cubic | 9.241 | 1 | 9.241 | .075 | .787 |
| | Quadratic | Linear | 358.524 | 1 | 358.524 | 2.930 | .104 |
| | | Quadratic | 41.559 | 1 | 41.559 | .218 | .646 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Cubic | 591.762 | 1 | 591.762 | 4.187 | .056 |
| | Cubic | Linear | 48.063 | 1 | 48.063 | .346 | .564 |
| | | Quadratic | 365.845 | 1 | 365.845 | 1.737 | .204 |
| | | Cubic | 46.689 | 1 | 46.689 | .842 | .371 |
| Error(processing*SNR) | Linear | Linear | 2348.892 | 18 | 130.494 | | |
| | | Quadratic | 1433.140 | 18 | 79.619 | | |
| | | Cubic | 2219.094 | 18 | 123.283 | | |
| | Quadratic | Linear | 2202.804 | 18 | 122.378 | | |
| | | Quadratic | 3427.317 | 18 | 190.407 | | |
| | | Cubic | 2543.849 | 18 | 141.325 | | |
| | Cubic | Linear | 2503.140 | 18 | 139.063 | | |
| | | Quadratic | 3792.069 | 18 | 210.671 | | |
| | | Cubic | 998.320 | 18 | 55.462 | | |

**Tests of Between-Subjects Effects**

Measure: MEASURE_1

Transformed Variable: Average

| Source | Type III Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Intercept | 817943.853 | 1 | 817943.853 | 280.433 | .000 |
| Group | 60933.751 | 1 | 60933.751 | 20.891 | .000 |

| | | | | | |
|---|---|---|---|---|---|
| Error | 52500.971 | 18 | 2916.721 | | |

## Estimated Marginal Means

**1. Grand Mean**

Measure: MEASURE_1

| Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|
| | | Lower Bound | Upper Bound |
| 50.558 | 3.019 | 44.215 | 56.900 |

## 2. Group

**Estimates**

Measure: MEASURE_1

| Group | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |
| HIA | 36.758 | 4.270 | 27.788 | 45.729 |
| NHA | 64.357 | 4.270 | 55.387 | 73.327 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) Group | (J) Group | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| HIA | NHA | -27.598* | 6.038 | .000 | -40.284 | -14.913 |
| NHA | HIA | 27.598* | 6.038 | .000 | 14.913 | 40.284 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Univariate Tests**

Measure: MEASURE_1

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 3808.359 | 1 | 3808.359 | 20.891 | .000 |
| Error | 3281.311 | 18 | 182.295 | | |

The F tests the effect of Group. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

## 3. processing

**Estimates**

Measure: MEASURE_1

| processing | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|
| | | | Lower Bound | Upper Bound |

| | | | | |
|---|---|---|---|---|
| 1 | 53.561 | 3.220 | 46.796 | 60.327 |
| 2 | 56.503 | 3.635 | 48.866 | 64.140 |
| 3 | 45.148 | 3.065 | 38.710 | 51.587 |
| 4 | 47.018 | 2.887 | 40.952 | 53.084 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|
| | | | | | Lower Bound | Upper Bound |
| 1 | 2 | -2.941 | 1.971 | .918 | -8.782 | 2.899 |
| | 3 | 8.413* | 1.632 | .000 | 3.579 | 13.247 |
| | 4 | 6.544* | 1.556 | .003 | 1.933 | 11.154 |
| 2 | 1 | 2.941 | 1.971 | .918 | -2.899 | 8.782 |
| | 3 | 11.355* | 1.923 | .000 | 5.658 | 17.051 |
| | 4 | 9.485* | 1.561 | .000 | 4.860 | 14.110 |
| 3 | 1 | -8.413* | 1.632 | .000 | -13.247 | -3.579 |
| | 2 | -11.355* | 1.923 | .000 | -17.051 | -5.658 |
| | 4 | -1.870 | 2.076 | 1.000 | -8.020 | 4.281 |
| 4 | 1 | -6.544* | 1.556 | .003 | -11.154 | -1.933 |
| | 2 | -9.485* | 1.561 | .000 | -14.110 | -4.860 |
| | 3 | 1.870 | 2.076 | 1.000 | -4.281 | 8.020 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .857 | 31.890[a] | 3.000 | 16.000 | .000 |
| Wilks' lambda | .143 | 31.890[a] | 3.000 | 16.000 | .000 |
| Hotelling's trace | 5.979 | 31.890[a] | 3.000 | 16.000 | .000 |
| Roy's largest root | 5.979 | 31.890[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate effect of processing. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 4. SNR

**Estimates**

Measure: MEASURE_1

| | | | 95% Confidence Interval | |
|---|---|---|---|---|
| SNR | Mean | Std. Error | Lower Bound | Upper Bound |
| 1 | 89.063 | 3.281 | 82.169 | 95.956 |
| 2 | 63.374 | 3.776 | 55.441 | 71.307 |
| 3 | 37.643 | 3.257 | 30.800 | 44.486 |
| 4 | 12.152 | 2.353 | 7.208 | 17.096 |

**Pairwise Comparisons**

Measure: MEASURE_1

| (I) SNR | (J) SNR | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|
| 1 | 2 | 25.689* | 1.915 | .000 | 20.014 | 31.364 |
| | 3 | 51.420* | 1.709 | .000 | 46.355 | 56.485 |
| | 4 | 76.911* | 1.898 | .000 | 71.289 | 82.533 |
| 2 | 1 | -25.689* | 1.915 | .000 | -31.364 | -20.014 |
| | 3 | 25.731* | 1.084 | .000 | 22.519 | 28.943 |
| | 4 | 51.222* | 2.166 | .000 | 44.805 | 57.638 |
| 3 | 1 | -51.420* | 1.709 | .000 | -56.485 | -46.355 |
| | 2 | -25.731* | 1.084 | .000 | -28.943 | -22.519 |
| | 4 | 25.491* | 1.669 | .000 | 20.546 | 30.436 |
| 4 | 1 | -76.911* | 1.898 | .000 | -82.533 | -71.289 |
| | 2 | -51.222* | 2.166 | .000 | -57.638 | -44.805 |
| | 3 | -25.491* | 1.669 | .000 | -30.436 | -20.546 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|
| Pillai's trace | .991 | 559.677[a] | 3.000 | 16.000 | .000 |
| Wilks' lambda | .009 | 559.677[a] | 3.000 | 16.000 | .000 |
| Hotelling's trace | 104.939 | 559.677[a] | 3.000 | 16.000 | .000 |
| Roy's largest root | 104.939 | 559.677[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate effect of SNR. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

## 5. Group * processing

**Estimates**

Measure: MEASURE_1

| | | | | 95% Confidence Interval | |
|---|---|---|---|---|---|
| Group | processing | Mean | Std. Error | Lower Bound | Upper Bound |
| HIA | 1 | 42.850 | 4.554 | 33.281 | 52.418 |
| | 2 | 39.360 | 5.141 | 28.560 | 50.160 |
| | 3 | 31.373 | 4.334 | 22.268 | 40.478 |
| | 4 | 33.451 | 4.083 | 24.873 | 42.029 |
| NHA | 1 | 64.273 | 4.554 | 54.705 | 73.842 |
| | 2 | 73.646 | 5.141 | 62.845 | 84.446 |
| | 3 | 58.924 | 4.334 | 49.818 | 68.029 |
| | 4 | 60.585 | 4.083 | 52.007 | 69.163 |

**Pairwise Comparisons**

Measure: MEASURE_1

| Group | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| HIA | 1 | 2 | 3.490 | 2.788 | 1.000 | -4.770 | 11.749 |
| | | 3 | 11.477* | 2.307 | .001 | 4.640 | 18.313 |
| | | 4 | 9.398* | 2.201 | .003 | 2.879 | 15.918 |
| | 2 | 1 | -3.490 | 2.788 | 1.000 | -11.749 | 4.770 |
| | | 3 | 7.987 | 2.719 | .053 | -.068 | 16.043 |
| | | 4 | 5.909 | 2.208 | .092 | -.632 | 12.449 |
| | 3 | 1 | -11.477* | 2.307 | .001 | -18.313 | -4.640 |
| | | 2 | -7.987 | 2.719 | .053 | -16.043 | .068 |
| | | 4 | -2.078 | 2.936 | 1.000 | -10.776 | 6.619 |
| | 4 | 1 | -9.398* | 2.201 | .003 | -15.918 | -2.879 |
| | | 2 | -5.909 | 2.208 | .092 | -12.449 | .632 |
| | | 3 | 2.078 | 2.936 | 1.000 | -6.619 | 10.776 |
| NHA | 1 | 2 | -9.372* | 2.788 | .021 | -17.631 | -1.113 |
| | | 3 | 5.350 | 2.307 | .194 | -1.486 | 12.186 |
| | | 4 | 3.689 | 2.201 | .666 | -2.831 | 10.208 |
| | 2 | 1 | 9.372* | 2.788 | .021 | 1.113 | 17.631 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | 3 | 14.722* | 2.719 | .000 | 6.667 | 22.778 |
| | 4 | 13.061* | 2.208 | .000 | 6.520 | 19.602 |
| 3 | 1 | -5.350 | 2.307 | .194 | -12.186 | 1.486 |
| | 2 | -14.722* | 2.719 | .000 | -22.778 | -6.667 |
| | 4 | -1.661 | 2.936 | 1.000 | -10.359 | 7.037 |
| 4 | 1 | -3.689 | 2.201 | .666 | -10.208 | 2.831 |
| | 2 | -13.061* | 2.208 | .000 | -19.602 | -6.520 |
| | 3 | 1.661 | 2.936 | 1.000 | -7.037 | 10.359 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| Group | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|
| HIA | Pillai's trace | .756 | 16.566[a] | 3.000 | 16.000 | .000 |
| | Wilks' lambda | .244 | 16.566[a] | 3.000 | 16.000 | .000 |
| | Hotelling's trace | 3.106 | 16.566[a] | 3.000 | 16.000 | .000 |
| | Roy's largest root | 3.106 | 16.566[a] | 3.000 | 16.000 | .000 |
| NHA | Pillai's trace | .777 | 18.558[a] | 3.000 | 16.000 | .000 |
| | Wilks' lambda | .223 | 18.558[a] | 3.000 | 16.000 | .000 |
| | Hotelling's trace | 3.480 | 18.558[a] | 3.000 | 16.000 | .000 |

| | | | | | |
|---|---|---|---|---|---|
| Roy's largest root | 3.480 | 18.558[a] | 3.000 | 16.000 | .000 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

**6. Group * SNR**

Measure: MEASURE_1

| Group | SNR | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| HIA | 1 | 74.324 | 4.640 | 64.575 | 84.073 |
| | 2 | 48.914 | 5.340 | 37.695 | 60.133 |
| | 3 | 22.909 | 4.606 | 13.231 | 32.586 |
| | 4 | .888 | 3.328 | -6.104 | 7.879 |
| NHA | 1 | 103.801 | 4.640 | 94.053 | 113.550 |
| | 2 | 77.833 | 5.340 | 66.614 | 89.052 |
| | 3 | 52.376 | 4.606 | 42.699 | 62.054 |
| | 4 | 23.416 | 3.328 | 16.425 | 30.408 |

**7. processing * SNR**

Measure: MEASURE_1

| processing | SNR | Mean | Std. Error | 95% Confidence Interval |
|---|---|---|---|---|

| | | | | Lower Bound | Upper Bound |
|---|---|---|---|---|---|
| 1 | 1 | 94.679 | 3.875 | 86.538 | 102.820 |
| | 2 | 61.818 | 4.057 | 53.295 | 70.342 |
| | 3 | 45.377 | 3.756 | 37.486 | 53.269 |
| | 4 | 12.371 | 2.998 | 6.074 | 18.669 |
| 2 | 1 | 97.123 | 2.927 | 90.974 | 103.272 |
| | 2 | 73.930 | 5.749 | 61.851 | 86.009 |
| | 3 | 44.692 | 5.111 | 33.955 | 55.430 |
| | 4 | 10.266 | 3.672 | 2.552 | 17.980 |
| 3 | 1 | 78.830 | 4.308 | 69.780 | 87.879 |
| | 2 | 53.142 | 3.630 | 45.515 | 60.769 |
| | 3 | 28.917 | 3.519 | 21.523 | 36.311 |
| | 4 | 19.705 | 3.333 | 12.703 | 26.707 |
| 4 | 1 | 85.618 | 4.029 | 77.153 | 94.083 |
| | 2 | 64.605 | 4.130 | 55.927 | 73.282 |
| | 3 | 31.584 | 3.296 | 24.659 | 38.508 |
| | 4 | 6.265 | 2.924 | .123 | 12.408 |

## 8. Group * processing * SNR

**Estimates**

Measure: MEASURE_1

| Group | processing | SNR | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|---|
| HIA | 1 | 1 | 83.413 | 5.480 | 71.899 | 94.926 |
| | | 2 | 52.893 | 5.737 | 40.839 | 64.947 |
| | | 3 | 32.613 | 5.312 | 21.453 | 43.773 |
| | | 4 | 2.479 | 4.239 | -6.427 | 11.386 |
| | 2 | 1 | 84.468 | 4.139 | 75.772 | 93.164 |
| | | 2 | 54.089 | 8.131 | 37.007 | 71.171 |
| | | 3 | 24.947 | 7.228 | 9.762 | 40.133 |
| | | 4 | -6.064 | 5.193 | -16.974 | 4.846 |
| | 3 | 1 | 63.464 | 6.092 | 50.666 | 76.263 |
| | | 2 | 37.321 | 5.134 | 26.534 | 48.107 |
| | | 3 | 17.856 | 4.977 | 7.400 | 28.313 |
| | | 4 | 6.851 | 4.713 | -3.052 | 16.753 |
| | 4 | 1 | 65.950 | 5.698 | 53.979 | 77.921 |
| | | 2 | 51.353 | 5.841 | 39.081 | 63.625 |
| | | 3 | 16.219 | 4.661 | 6.426 | 26.012 |
| | | 4 | .284 | 4.135 | -8.402 | 8.971 |
| NHA | 1 | 1 | 105.946 | 5.480 | 94.433 | 117.459 |
| | | 2 | 70.743 | 5.737 | 58.689 | 82.797 |
| | | 3 | 58.142 | 5.312 | 46.981 | 69.302 |

| | | | | | |
|---|---|---|---|---|---|
| | 4 | 22.263 | 4.239 | 13.357 | 31.169 |
| 2 | 1 | 109.778 | 4.139 | 101.082 | 118.474 |
| | 2 | 93.771 | 8.131 | 76.689 | 110.853 |
| | 3 | 64.438 | 7.228 | 49.252 | 79.623 |
| | 4 | 26.596 | 5.193 | 15.686 | 37.506 |
| 3 | 1 | 94.195 | 6.092 | 81.397 | 106.993 |
| | 2 | 68.963 | 5.134 | 58.177 | 79.749 |
| | 3 | 39.978 | 4.977 | 29.521 | 50.434 |
| | 4 | 32.559 | 4.713 | 22.657 | 42.461 |
| 4 | 1 | 105.287 | 5.698 | 93.316 | 117.258 |
| | 2 | 77.856 | 5.841 | 65.585 | 90.128 |
| | 3 | 46.949 | 4.661 | 37.155 | 56.742 |
| | 4 | 12.247 | 4.135 | 3.560 | 20.933 |

**Pairwise Comparisons**

Measure: MEASURE_1

| Group | SNR | (I) processing | (J) processing | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Lower Bound | Upper Bound |
| HIA | 1 | 1 | 2 | -1.056 | 3.401 | 1.000 | -11.132 | 9.021 |
| | | | 3 | 19.948* | 4.867 | .004 | 5.529 | 34.368 |
| | | | 4 | 17.463* | 4.231 | .004 | 4.926 | 30.000 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 2 | 1 | 1.056 | 3.401 | 1.000 | -9.021 | 11.132 |
| | | 3 | 21.004* | 4.477 | .001 | 7.740 | 34.268 |
| | | 4 | 18.519* | 4.700 | .006 | 4.594 | 32.443 |
| | 3 | 1 | -19.948* | 4.867 | .004 | -34.368 | -5.529 |
| | | 2 | -21.004* | 4.477 | .001 | -34.268 | -7.740 |
| | | 4 | -2.485 | 5.212 | 1.000 | -17.926 | 12.955 |
| | 4 | 1 | -17.463* | 4.231 | .004 | -30.000 | -4.926 |
| | | 2 | -18.519* | 4.700 | .006 | -32.443 | -4.594 |
| | | 3 | 2.485 | 5.212 | 1.000 | -12.955 | 17.926 |
| 2 | 1 | 2 | -1.196 | 6.664 | 1.000 | -20.940 | 18.549 |
| | | 3 | 15.572* | 4.656 | .022 | 1.778 | 29.367 |
| | | 4 | 1.540 | 4.830 | 1.000 | -12.771 | 15.851 |
| | 2 | 1 | 1.196 | 6.664 | 1.000 | -18.549 | 20.940 |
| | | 3 | 16.768 | 6.206 | .088 | -1.620 | 35.156 |
| | | 4 | 2.736 | 5.137 | 1.000 | -12.484 | 17.955 |
| | 3 | 1 | -15.572* | 4.656 | .022 | -29.367 | -1.778 |
| | | 2 | -16.768 | 6.206 | .088 | -35.156 | 1.620 |
| | | 4 | -14.032 | 5.237 | .092 | -29.549 | 1.485 |
| | 4 | 1 | -1.540 | 4.830 | 1.000 | -15.851 | 12.771 |
| | | 2 | -2.736 | 5.137 | 1.000 | -17.955 | 12.484 |
| | | 3 | 14.032 | 5.237 | .092 | -1.485 | 29.549 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 3 | 1 | 2 | 7.666 | 5.213 | .952 | -7.779 | 23.111 |
| | | 3 | 14.757* | 4.452 | .023 | 1.567 | 27.946 |
| | | 4 | 16.394* | 5.200 | .033 | .987 | 31.802 |
| | 2 | 1 | -7.666 | 5.213 | .952 | -23.111 | 7.779 |
| | | 3 | 7.091 | 4.730 | .907 | -6.922 | 21.104 |
| | | 4 | 8.728 | 6.473 | 1.000 | -10.449 | 27.906 |
| | 3 | 1 | -14.757* | 4.452 | .023 | -27.946 | -1.567 |
| | | 2 | -7.091 | 4.730 | .907 | -21.104 | 6.922 |
| | | 4 | 1.638 | 5.482 | 1.000 | -14.604 | 17.879 |
| | 4 | 1 | -16.394* | 5.200 | .033 | -31.802 | -.987 |
| | | 2 | -8.728 | 6.473 | 1.000 | -27.906 | 10.449 |
| | | 3 | -1.638 | 5.482 | 1.000 | -17.879 | 14.604 |
| 4 | 1 | 2 | 8.543 | 5.116 | .673 | -6.613 | 23.700 |
| | | 3 | -4.371 | 4.878 | 1.000 | -18.823 | 10.080 |
| | | 4 | 2.195 | 3.332 | 1.000 | -7.676 | 12.067 |
| | 2 | 1 | -8.543 | 5.116 | .673 | -23.700 | 6.613 |
| | | 3 | -12.915 | 6.028 | .277 | -30.775 | 4.946 |
| | | 4 | -6.348 | 5.711 | 1.000 | -23.267 | 10.571 |
| | 3 | 1 | 4.371 | 4.878 | 1.000 | -10.080 | 18.823 |
| | | 2 | 12.915 | 6.028 | .277 | -4.946 | 30.775 |
| | | 4 | 6.566 | 5.457 | 1.000 | -9.601 | 22.734 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 4 | 1 | -2.195 | 3.332 | 1.000 | -12.067 | 7.676 |
| | | | 2 | 6.348 | 5.711 | 1.000 | -10.571 | 23.267 |
| | | | 3 | -6.566 | 5.457 | 1.000 | -22.734 | 9.601 |
| NHA | 1 | 1 | 2 | -3.832 | 3.401 | 1.000 | -13.908 | 6.244 |
| | | | 3 | 11.751 | 4.867 | .160 | -2.668 | 26.170 |
| | | | 4 | .659 | 4.231 | 1.000 | -11.878 | 13.196 |
| | | 2 | 1 | 3.832 | 3.401 | 1.000 | -6.244 | 13.908 |
| | | | 3 | 15.583* | 4.477 | .016 | 2.319 | 28.847 |
| | | | 4 | 4.491 | 4.700 | 1.000 | -9.434 | 18.416 |
| | | 3 | 1 | -11.751 | 4.867 | .160 | -26.170 | 2.668 |
| | | | 2 | -15.583* | 4.477 | .016 | -28.847 | -2.319 |
| | | | 4 | -11.092 | 5.212 | .284 | -26.533 | 4.349 |
| | | 4 | 1 | -.659 | 4.231 | 1.000 | -13.196 | 11.878 |
| | | | 2 | -4.491 | 4.700 | 1.000 | -18.416 | 9.434 |
| | | | 3 | 11.092 | 5.212 | .284 | -4.349 | 26.533 |
| | 2 | 1 | 2 | -23.028* | 6.664 | .017 | -42.772 | -3.283 |
| | | | 3 | 1.780 | 4.656 | 1.000 | -12.014 | 15.575 |
| | | | 4 | -7.113 | 4.830 | .949 | -21.424 | 7.198 |
| | | 2 | 1 | 23.028* | 6.664 | .017 | 3.283 | 42.772 |
| | | | 3 | 24.808* | 6.206 | .005 | 6.420 | 43.196 |
| | | | 4 | 15.915* | 5.137 | .037 | .695 | 31.134 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 3 | 1 | -1.780 | 4.656 | 1.000 | -15.575 | 12.014 |
| | | 2 | -24.808* | 6.206 | .005 | -43.196 | -6.420 |
| | | 4 | -8.894 | 5.237 | .640 | -24.411 | 6.624 |
| | 4 | 1 | 7.113 | 4.830 | .949 | -7.198 | 21.424 |
| | | 2 | -15.915* | 5.137 | .037 | -31.134 | -.695 |
| | | 3 | 8.894 | 5.237 | .640 | -6.624 | 24.411 |
| 3 | 1 | 2 | -6.296 | 5.213 | 1.000 | -21.741 | 9.149 |
| | | 3 | 18.164* | 4.452 | .004 | 4.974 | 31.354 |
| | | 4 | 11.193 | 5.200 | .271 | -4.215 | 26.601 |
| | 2 | 1 | 6.296 | 5.213 | 1.000 | -9.149 | 21.741 |
| | | 3 | 24.460* | 4.730 | .000 | 10.447 | 38.473 |
| | | 4 | 17.489 | 6.473 | .088 | -1.688 | 36.666 |
| | 3 | 1 | -18.164* | 4.452 | .004 | -31.354 | -4.974 |
| | | 2 | -24.460* | 4.730 | .000 | -38.473 | -10.447 |
| | | 4 | -6.971 | 5.482 | 1.000 | -23.212 | 9.271 |
| | 4 | 1 | -11.193 | 5.200 | .271 | -26.601 | 4.215 |
| | | 2 | -17.489 | 6.473 | .088 | -36.666 | 1.688 |
| | | 3 | 6.971 | 5.482 | 1.000 | -9.271 | 23.212 |
| 4 | 1 | 2 | -4.333 | 5.116 | 1.000 | -19.489 | 10.824 |
| | | 3 | -10.296 | 4.878 | .294 | -24.748 | 4.155 |
| | | 4 | 10.016* | 3.332 | .045 | .145 | 19.888 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | 1 | 4.333 | 5.116 | 1.000 | -10.824 | 19.489 |
| | 3 | -5.963 | 6.028 | 1.000 | -23.824 | 11.897 |
| | 4 | 14.349 | 5.711 | .130 | -2.570 | 31.269 |
| 3 | 1 | 10.296 | 4.878 | .294 | -4.155 | 24.748 |
| | 2 | 5.963 | 6.028 | 1.000 | -11.897 | 23.824 |
| | 4 | 20.312* | 5.457 | .009 | 4.145 | 36.480 |
| 4 | 1 | -10.016* | 3.332 | .045 | -19.888 | -.145 |
| | 2 | -14.349 | 5.711 | .130 | -31.269 | 2.570 |
| | 3 | -20.312* | 5.457 | .009 | -36.480 | -4.145 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

**Multivariate Tests**

| Group | SNR | | Value | F | Hypothesis df | Error df | Sig. |
|---|---|---|---|---|---|---|---|
| HIA | 1 | Pillai's trace | .647 | 9.777[a] | 3.000 | 16.000 | .001 |
| | | Wilks' lambda | .353 | 9.777[a] | 3.000 | 16.000 | .001 |
| | | Hotelling's trace | 1.833 | 9.777[a] | 3.000 | 16.000 | .001 |
| | | Roy's largest root | 1.833 | 9.777[a] | 3.000 | 16.000 | .001 |
| | 2 | Pillai's trace | .449 | 4.338[a] | 3.000 | 16.000 | .020 |
| | | Wilks' lambda | .551 | 4.338[a] | 3.000 | 16.000 | .020 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Hotelling's trace | .813 | 4.338[a] | 3.000 | 16.000 | .020 |
| | | Roy's largest root | .813 | 4.338[a] | 3.000 | 16.000 | .020 |
| | 3 | Pillai's trace | .463 | 4.607[a] | 3.000 | 16.000 | .017 |
| | | Wilks' lambda | .537 | 4.607[a] | 3.000 | 16.000 | .017 |
| | | Hotelling's trace | .864 | 4.607[a] | 3.000 | 16.000 | .017 |
| | | Roy's largest root | .864 | 4.607[a] | 3.000 | 16.000 | .017 |
| | 4 | Pillai's trace | .222 | 1.524[a] | 3.000 | 16.000 | .247 |
| | | Wilks' lambda | .778 | 1.524[a] | 3.000 | 16.000 | .247 |
| | | Hotelling's trace | .286 | 1.524[a] | 3.000 | 16.000 | .247 |
| | | Roy's largest root | .286 | 1.524[a] | 3.000 | 16.000 | .247 |
| NHA | 1 | Pillai's trace | .407 | 3.666[a] | 3.000 | 16.000 | .035 |
| | | Wilks' lambda | .593 | 3.666[a] | 3.000 | 16.000 | .035 |
| | | Hotelling's trace | .687 | 3.666[a] | 3.000 | 16.000 | .035 |
| | | Roy's largest root | .687 | 3.666[a] | 3.000 | 16.000 | .035 |
| | 2 | Pillai's trace | .485 | 5.022[a] | 3.000 | 16.000 | .012 |
| | | Wilks' lambda | .515 | 5.022[a] | 3.000 | 16.000 | .012 |
| | | Hotelling's trace | .942 | 5.022[a] | 3.000 | 16.000 | .012 |
| | | Roy's largest root | .942 | 5.022[a] | 3.000 | 16.000 | .012 |
| | 3 | Pillai's trace | .649 | 9.860[a] | 3.000 | 16.000 | .001 |
| | | Wilks' lambda | .351 | 9.860[a] | 3.000 | 16.000 | .001 |
| | | Hotelling's trace | 1.849 | 9.860[a] | 3.000 | 16.000 | .001 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | Roy's largest root | 1.849 | 9.860[a] | 3.000 | 16.000 | .001 |
| | 4 | Pillai's trace | .475 | 4.820[a] | 3.000 | 16.000 | .014 |
| | | Wilks' lambda | .525 | 4.820[a] | 3.000 | 16.000 | .014 |
| | | Hotelling's trace | .904 | 4.820[a] | 3.000 | 16.000 | .014 |
| | | Roy's largest root | .904 | 4.820[a] | 3.000 | 16.000 | .014 |

Each F tests the multivariate simple effects of processing within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic

# Appendix E: Research Ethics

Western Research

Research Ethics

**Western University Health Science Research Ethics Board**
**HSREB Annual Continuing Ethics Approval Notice**

**Date**: October 10, 2016
**Principal Investigator**: Dr. Prudence Allen
**Department & Institution:** Health Sciences\Communication Sciences & Disorders,Western University

**Review Type:** Delegated
**HSREB File Number:** 6551
**Study Title:** Testing the efficacy and efficiency of an improved comprehensive test battery for the assessment of auditory processing disorders.
**Sponsor:** Ontario Research fund

**HSREB Renewal Due Date & HSREB Expiry Date:**
Renewal Due -2017/09/30
Expiry Date -2017/10/27

The Western University Health Science Research Ethics Board (HSREB) has reviewed the Continuing Ethics Review (CER) Form and is re-issuing approval for the above noted study.

The Western University HSREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the International Conference on Harmonization of Technical Requirements for Registration of Pharmaceuticals for Human Use Guideline for Good Clinical Practice (ICH E6 R1), the Ontario Freedom of Information and Protection of Privacy Act (FIPPA, 1990), the Ontario Personal Health Information Protection Act (PHIPA, 2004), Part 4 of the Natural Health Product Regulations, Health Canada Medical Device Regulations and Part C, Division 5, of the Food and Drug Regulations of Health Canada.

Members of the HSREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The HSREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000940.

**Western University, Research,** Support Services Bldg., Rm. 5150
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# Appendix F: Subjective and Objective Assessment Results

**Table E-1: Averaged speech intelligibility scores for children with suspected APD (Figure 3-8).**

| LSNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.95 | 0.91 | 0.92 | 0.87 |
| Tau = 0.0001 | 0.99 | 0.97 | 0.97 | 0.82 |
| Tau = 0.001 | 0.98 | 0.94 | 0.89 | 0.65 |
| UP | 0.95 | 0.87 | 0.63 | 0.18 |

**Table E-2: Averaged speech intelligibility scores for children with NH (Figure 3-9).**

| LSNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.97 | 0.96 | 0.98 | 0.95 |
| Tau = 0.0001 | 1 | 0.99 | 0.98 | 0.91 |
| Tau = 0.001 | 0.98 | 0.98 | 0.91 | 0.73 |
| UP | 0.97 | 0.87 | 0.82 | 0.26 |

**Table E-3: Averaged speech intelligibility scores for adults with NH (Figure 3-10).**

| LSNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.99 | 0.99 | 0.99 | 0.96 |
| Tau = 0.0001 | 0.99 | 0.99 | 0.99 | 0.96 |
| Tau = 0.001 | 1 | 0.98 | 0.98 | 0.78 |
| UP | 1 | 0.92 | 0.81 | 0.33 |

**Table E-4: Objective assessment of the dynamic EE for LSNR = -6 dB in the presence of SSN with no NR (Figure 3-15).**

| SSNR (dB) / processing | 15 | 10 | 5 | 0 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.69 | 0.47 | 0.27 | 0.21 |
| Tau = 0.0001 | 0.64 | 0.50 | 0.22 | 0.20 |
| Tau = 0.001 | 0.74 | 0.63 | 0.31 | 0.20 |
| UP | 0.18 | 0.18 | 0.18 | 0.19 |

**Table E-5: Objective assessment of the dynamic EE for LSNR = -6 dB in the presence of MTBN with no NR (Figure 3-16).**

| SSNR (dB) / Processing | 15 | 10 | 5 | 0 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.76 | 0.56 | 0.42 | 0.20 |
| Tau = 0.0001 | 0.79 | 0.60 | 0.30 | 0.19 |
| Tau = 0.001 | 0.56 | 0.55 | 0.26 | 0.18 |
| UP | 0.23 | 0.22 | 0.23 | 0.23 |

**Table E-6: Objective assessment of the dynamic EE for LSNR = -6 dB in the presence of SSN with logMMSE NR (Figure 3-17).**

| SSNR (dB) / Processing | 15 | 10 | 5 | 0 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.32 | 0.21 | 0.21 | 0.22 |
| Tau = 0.0001 | 0.29 | 0.20 | 0.21 | 0.23 |
| Tau = 0.001 | 0.22 | 0.21 | 0.21 | 0.23 |
| UP | 0.21 | 0.21 | 0.22 | 0.23 |

**Table E-7: Objective assessment of the dynamic EE for LSNR = -6 dB in the presence of MTBN with logMMSE NR (Figure 3-18).**

| SSNR (dB) / Processing | 15 | 10 | 5 | 0 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.78 | 0.50 | 0.24 | 0.20 |
| Tau = 0.0001 | 0.72 | 0.64 | 0.19 | 0.20 |
| Tau = 0.001 | 0.44 | 0.41 | 0.26 | 0.23 |
| UP | 0.21 | 0.27 | 0.23 | 0.23 |

**Table E-8: Objective assessment of the dynamic EE for LSNR = -6 dB in the presence of SSN with MHA NR (Figure 3-19).**

| SSNR (dB) / Processing | 15 | 10 | 5 | 0 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.33 | 0.23 | 0.21 | 0.22 |
| Tau = 0.0001 | 0.27 | 0.21 | 0.21 | 0.22 |
| Tau = 0.001 | 0.26 | 0.21 | 0.22 | 0.23 |
| UP | 0.21 | 0.21 | 0.22 | 0.23 |

**Table E-9: Objective assessment of the dynamic EE for LSNR = -6 dB in the presence of MTBN with MHA NR (Figure 3-20).**

| SSNR (dB) / Processing | 15 | 10 | 5 | 0 |
|---|---|---|---|---|
| Tau = 0.00001 | 0.81 | 0.64 | 0.36 | 0.19 |
| Tau = 0.0001 | 0.66 | 0.62 | 0.43 | 0.23 |
| Tau = 0.001 | 0.48 | 0.36 | 0.29 | 0.21 |
| UP | 0.22 | 0.28 | 0.20 | 0.22 |

**Table E-10: Averaged speech intelligibility scores for children with APD in the presence of SSN (Figure 4-5).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| SEE | 0.79 | 0.66 | 0.40 | 0.08 |
| logMMSESEE | 0.58 | 0.58 | 0.29 | 0.11 |
| MHASEE | 0.82 | 0.67 | 0.47 | 0.21 |
| UP | 0.91 | 0.66 | 0.31 | 0.10 |

**Table E-11: Averaged speech intelligibility scores for children with NH in the presence of SSN (Figure 4-6).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| SEE | 0.82 | 0.77 | 0.47 | 0.10 |
| logMMSESEE | 0.62 | 0.62 | 0.38 | 0.14 |
| MHASEE | 0.84 | 0.7 | 0.45 | 0.26 |
| UP | 0.96 | 0.83 | 0.50 | 0.20 |

**Table E-12: Averaged speech intelligibility scores for children with APD in the presence of MTBN (Figure 4-7).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| SEE | 0.57 | 0.34 | 0.1 | 0.04 |
| logMMSESEE | 0.51 | 0.23 | 0.07 | 0.01 |
| MHASEE | 0.42 | 0.23 | 0.11 | 0.03 |
| UP | 0.85 | 0.58 | 0.37 | 0.05 |

**Table E-13: Objective assessment of companding algorithm in the presence of SSN (Figure 5-13).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Companding | 0.78 | 0.29 | 0.24 | 0.16 |
| MHACompanding | 0.88 | 0.85 | 0.67 | 0.54 |
| UP | 0.71 | 0.59 | 0.37 | 0.15 |

**Table E-14: Objective assessment of companding algorithm in the presence of MTBN (Figure 5-14).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Companding | 0.81 | 0.43 | 0.31 | 0.3 |
| MHACompanding | 0.93 | 0.79 | 0.73 | 0.53 |
| UP | 0.82 | 0.76 | 0.58 | 0.3 |

**Table E-15: Averaged speech intelligibility scores for adults with NH in the presence of SSN (Figure 6-3).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Dichotic | 0.98 | 0.96 | 0.72 | 0.44 |
| MHA | 0.97 | 0.94 | 0.81 | 0.41 |
| MHADichotic | 0.98 | 0.95 | 0.67 | 0.39 |
| UP | 0.97 | 0.89 | 0.68 | 0.22 |

**Table E-16: Averaged speech intelligibility scores for adults with HI in the presence of SSN (Figure 6-4).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Dichotic | 0.80 | 0.73 | 0.33 | 0.16 |
| MHA | 0.69 | 0.53 | 0.50 | 0.1 |
| MHADichotic | 0.66 | 0.83 | 0.37 | 0.10 |
| UP | 0.86 | 0.76 | 0.35 | 0.08 |

**Table E-17: Averaged speech intelligibility scores for adults with NH in the presence of MTBN (Figure 6-5).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Dichotic | 0.96 | 0.89 | 0.64 | 0.26 |
| MHA | 0.90 | 0.69 | 0.39 | 0.32 |
| MHADichotic | 0.93 | 0.77 | 0.46 | 0.14 |
| UP | 0.96 | 0.70 | 0.58 | 0.22 |

**Table E-18: Averaged speech intelligibility scores for adults with HI in the presence of MTBN (Figure 6-6).**

| SNR (dB) / Processing | 3 | 0 | -3 | -6 |
|---|---|---|---|---|
| Dichotic | 0.82 | 0.56 | 0.28 | 0.06 |
| MHA | 0.62 | 0.37 | 0.19 | 0.12 |
| MHADichotic | 0.65 | 0.51 | 0.19 | 0.07 |
| UP | 0.79 | 0.52 | 0.33 | 0.09 |

# Curriculum Vitae

| | |
|---|---|
| **Name:** | Farid Moshgelani |
| **Education and Degrees:** | Western University<br>London, Ontario, Canada<br>2014-2018 Ph.D., Electrical Engineering<br><br>Royal Military College of Canada<br>Kingston, Ontario, Canada<br>2010-2012 M.Sc., Computer Engineering<br><br>Malek-Ashtar University of Technology, Isfahan, Iran<br>1999-2003 B.Sc., Electrical Engineering |
| **Honors and Awards:** | Canadian Acoustics Student Researcher Travel Bursaries<br>2017<br><br>Western Graduate Scholarship (WGRS), UWO, London, Canada 2014-2018 |
| **Working Experience:** | Research Assistant<br>National Centre for Audiology, London, Ontario, Canada<br>2014-2018<br><br>Research Intern<br>AMD, Toronto, Ontario, Canada<br>Summer 2016<br><br>Research Assistant<br>Carleton University, Electronic Department<br>Ottawa, Ontario, Canada<br>2013-2014<br><br>Research Assistant<br>Royal Military College of Canada, Electrical and Computer Engineering Department<br>Kingston, Ontario, Canada<br>2010- 2012<br><br>Research Assistant<br>Queens University, Electrical and Computer Engineering Department<br>Kingston, Ontario, Canada<br>Summer 2013 |

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**Journal Papers**

**Farid Moshgelani**, Vijay Parsa, Chris Allan, Sangamanatha Ankmnal Veeranna, Prudence Allen, *Objective and Subjective Assessment of Envelope Enhancement Algorithms for Assistive Hearing Devices*. Biomed. Signal Proc. and Control 47: 16-25 (2019)

**Farid Moshgelani**, Vijay Parsa, *Objective Assessment of Companding Architecture for Assistive Hearing Devices*. Canadian Acoustical Association Journal 45: 138-139 (2017)

**Farid Moshgelani**, Dhamin Al-Khalili, and Come Rozon, *Low Leakage MUX/XOR Functions using Symmetric and Asymmetric FinFETs*, the World Academy of Science, Engineering and Technology Journal, No. 0076, pp. 51-56, 2013

**Farid Moshgelani**, Dhamin Al-Khalili, and Come Rozon, *Ultra-Low Leakage Arithmetic Circuits using Symmetric and Asymmetric FinFETs*, Journal of Electrical and Computer Engineering, *2013*

**Conference Papers**

**Farid Moshgelani**, Vijay Parsa:
"Objective Assessment of Envelope Enhancement Algorithms for Assistive Hearing Devices", GlobalSIP 2017: 447-451

**Farid Moshgelani**, Dhamin Al-Khalili, Come Rozon,
Ultra Low Leakage Structures for Logic Circuits using Symmetric and Asymmetric FinFETs. NEWCAS 2012: 385-388

**Farid Moshgelani**, Dhamin Al-Khalili, and Come Rozon, "Low Leakage MUX/XOR Functions using Symmetric and Asymmetric FinFETs" in the proceeding of International Conference on Computer, Electrical, and Systems Sciences, and Engineering, Venice, Italy, pp. 286-291, April 2013.

**Farid Moshgelani**, Dhamin Al-Khalili, and Come Rozon, "Adder Circuits using Symmetric and Asymmetric FinFETs" in the proceeding of IEEE International Conference on Advances in Industrial Control, Electronics and Computer Engineering (AICECE), pp. 411-414, May 2013.