

Japanese speech intelligibility estimation and prediction using objective intelligibility indices under noisy and reverberant conditions

著者	KOBAYASHI Yosuke, KONDO Kazuhiro
journal or publication title	Applied Acoustics
volume	156
year	2019-12-15
URL	http://hdl.handle.net/10258/00010010

doi: info:doi/10.1016/j.apacoust.2019.07.034

Japanese speech intelligibility estimation and prediction using objective intelligibility indices under noisy and reverberant conditions

Yosuke Kobayashi^{a,*}, Kazuhiro Kondo^b

^a*Graduate School of Engineering, Muroran Institute of Technology
27-1 Mizumoto, Muroran, Hokkaido 050-8585, Japan*

^b*Graduate School of Science and Engineering, Yamagata University,
4-3-16 Jonan, Yonezawa, Yamagata, Japan*

Abstract

Objective measures of intelligibility are preferable to subjective ones in the evaluation of speech systems used in real environments. In this study, subjective evaluations of eight types of indoor noise environments were used to compare four intelligibility indices to objectively evaluate Japanese speech intelligibility. These indices were as follows: short-time objective intelligibility (STOI), which has been widely used in recent years; speech intelligibility prediction based on mutual information (SIMI), which is derived from STOI; extended STOI (ES-TOI), which is an improved version of STOI; and frequency weighted segmental signal to noise ratio (fwSNRseg), which incorporates both time and frequency components. These indices were subjectively evaluated in the eight noisy environments included in the corpus and environments for noisy speech recognition 4 (CENSREC-4) dataset using the familiarity-controlled word lists 2007 (FW07) as the speech data for the intelligibility evaluations. The results of the subjective evaluation of the four indices were then used to train predictive intelligibility estimation models. We evaluated the model performance using cross validation, which involved repeated training of seven of the eight environments and predicting the speech intelligibility under the remaining one environment. In the

*Corresponding author

Email address: ykobayashi@csse.muroran-it.ac.jp (Yosuke Kobayashi)

simulation results, the prediction accuracy of the SIMI index was significantly higher than that of the other indices, with a root mean squared error of 0.160 and a correlation coefficient of 0.934.

Keywords: Speech intelligibility, Intelligibility index, STOI, SIMI, ESTOI, fwSNRseg

1. Introduction

The intelligibility of the output from a speech system used in a real environment is influenced by factors such as the transfer characteristics of the environment in which it is used and the background noise. Accordingly, speech systems are developed in environments without people, as it is impossible to predict the background noise and reverberations that will occur during actual use. Moreover, it is difficult to predict the intelligibility, especially when the system is operated in environments with high levels of background noise and reverberations such as train stations, airports, and schools. Thus, speech intelligibility prediction that simulates the use of speech systems in real environments is indispensable. This study focused on estimating the intelligibility of a public address (PA) system in indoor environments. As PA systems do not usually employ noise reduction techniques such as those used in hearing aids, noise and reverberation directly affect intelligibility.

Conventionally, researchers have used the articulation index (AI) [1] proposed by French and Steinberg to indicate the intelligibility of speech. The AI was further modified by Kryter [2] and standardized by ANSI. Currently, the AI is known as the speech intelligibility index (SII) [3, 4]. The SII is based on the AI with the difference that critical bands are used for analysis in the SII. The AI/SII assumes that the signal to noise ratio (SNR) at each band of auditory perception contributes independently to articulation. Thus, the calculation of AI/SII uses the average value of the SNR of each band, where perceptual weighting is used, and the SNR is normalized to a value between 0 and 1. The speech transmission index (STI) [5] was proposed by Steeneken and

25 Houtgast and standardized by ISO/IEC [6]. The STI models the transduction
26 pathway of the speech using a modulation transfer function (MTF) and mea-
27 sures the intelligibility based on changes to the MTF. In particular, the STI is
28 based on the principle that reverberation and added noise tend to reduce the
29 time amplitude/intensity modulation depth compared with a clean probe signal.
30 The STI is used to evaluate the speech transmission quality according to the
31 acoustic characteristics of the channel.

32 These indices represent standardized measures that have been used over a
33 long period of time with continuous minor improvements. However, they are
34 not necessarily suitable for evaluating the intelligibility of all types of degraded
35 speech. Recently, frequency weighted segmental SNR (fwSNRseg) [7] was pro-
36 posed by Jianfen Ma et al. This intelligibility index is based on the SNRs of
37 segmented speech signals, and it incorporates both time and frequency weights.
38 Therefore, it can be thought of as an extension of the AI into the time domains.

39 The short-time objective intelligibility (STOI) measure was proposed by
40 Taal et al. [8]. STOI is based on correlation coefficients between the clean
41 speech and degraded speech power spectral envelopes using one-third octave
42 bands. Therefore, STOI is not based on the SNR; it can be used to estimate
43 the speech intelligibility as well as musical noise by a noise reduction algorithm.
44 Extensions of the STOI are the speech intelligibility prediction based on mutual
45 information (SIMI) [9] and the extended STOI (ESTOI) [10]. SIMI is based on
46 information theory concepts such as entropy and mutual information [11]. ES-
47 TOI calculates the speech intelligibility without assuming mutual independence
48 between frequency bands, unlike the correlation in STOI.

49 Rather than relying on the global SNR in transitional segments of speech
50 signals, STOI-type indices use processing over short time periods to account
51 for subtle changes in the frequency characteristics. Although speech systems
52 used in PA systems, which is the main target of our study, do not perform noise
53 reduction, they are used in environments with non-stationary background noise.
54 Thus, STOI-type indices that assume non-stationary noise are likely to provide
55 more realistic evaluations than AI/SII and STI, which are based on the SNR

56 and assume only stationary noise sources. By comparing the effect of the band-
57 importance function based on the auditory model used in fwSNRseg [7] with
58 that of the STOI-type indices we aim to identify the most effective intelligibility
59 indicator with outdoor noise and reverberation environment.

60 In contrast, the subjective evaluation result of intelligibility is not language
61 dependent on a global level; however, its stability depends extensively on the
62 mother tongue (native language) of the listener. J. Li et al. compared multiple
63 objective intelligibility estimation results of noise suppressed speech in Mandarin
64 and Japanese [12]. The evaluation showed that it is more difficult to estimate
65 Japanese intelligibility than Mandarin intelligibility using fwSNRseg and STOI.
66 Accordingly, owing to the influence of the native language of the listener; we
67 focused on Japanese intelligibility, as it is easy to collect subjects of the same
68 native language. We expect that the trend of the results of this study can be
69 broadly applied to other languages.

70 We have studied two approaches to speech intelligibility estimation. One
71 was intelligibility estimation such as the STOI-type indicator for cases where a
72 reference speech signal is available. We believe that highly accurate estimation
73 is possible with this method because it can clearly calculate the degradation of
74 the signal as a difference based on the reference speech signal. For example,
75 Kondo used the traditional fwSNRseg measure to estimate Japanese speech in-
76 telligibility under noisy environments and obtained superior performance over
77 traditional indices [13]. We expect the more recent STOI-type indices to outper-
78 form traditional ones in estimating the speech intelligibility of a speech system
79 (including a PA system) or similar application in a noisy environment.

80 Another intelligibility estimation approach is the non-reference type of esti-
81 mation, which does not use a reference signal [14, 15]. We believe that such
82 approaches have high practicality because the intelligibility can be determined
83 using only the broadcast speech. However, there are some limitations. To
84 overcome these, various factors must be optimized. In particular, in previous
85 research [15], we performed the evaluation considering the intelligibility of re-
86 verberant speech; however, we did not comprehensively evaluate a wide range

87 of reverberation and noise combinations. The present study provides the basic
88 analysis results necessary to improve the method for the estimation of non-
89 reference type intelligibility.

90 This paper describes the use of four indices including STOI-type indica-
91 tors to train the estimation models of Japanese speech intelligibility in noisy
92 environments. To use the STOI-type indicators targeting additive noise, we
93 assumed reverberation to be included as one form of noise. Eight noisy environ-
94 ments included in the Corpus and Environments for Noisy Speech Recognition 4
95 (CENSREC-4) [16] were used to reproduce noisy speech environments including
96 reverberation. In addition, The NTT-Tohoku university familiarity-controlled
97 word lists 2007 (FW07) [17] was used as the speech data for the subjective eval-
98 uation of Japanese speech intelligibility. Moreover, the intelligibility prediction
99 models were trained for the four intelligibility indices and their performance was
100 evaluated based on the subjective evaluation results. We evaluated the model
101 performance by using cross validation (CV), which is the repeated training of
102 the models in seven of the eight environments, and prediction of speech intel-
103 ligibility under the remaining one environment, to compare the performance
104 of these indices. CV evaluation was selected because the model must predict
105 conditions that were unknown when it was created. The practicality and ro-
106 bustness of the trained model is evaluated. The CV results show that the speech
107 intelligibility is predictable with a relatively high accuracy, which indicates that
108 the intelligibility estimation model can be used to evaluate the intelligibility of
109 speech systems in a real sound field. If such a high performance model is widely
110 used, the speech quality of announcements using speech systems will improve
111 at train stations, airports, and other public places.

112 The remainder of this paper is structured as follows. Intelligibility indices
113 used in the study are described in section 2, and the subjective evaluation is
114 described in section 3. These topics are integrated in section 4, where the results
115 of the intelligibility prediction experiment are described. Finally, a summary is
116 presented in section 5.

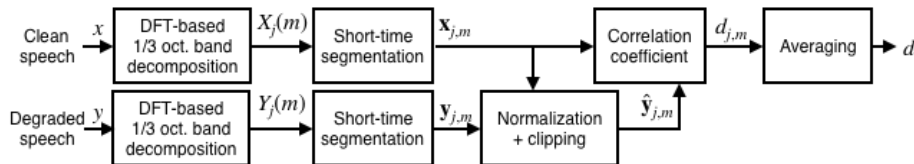


Figure 1: Flowchart of STOI calculation

117 2. Intelligibility indices

118 2.1. Objective intelligibility model

119 This research presents a subjective intelligibility evaluation followed by an
 120 objective prediction of the measured intelligibility. In this section, we explain the
 121 indices used in this research. Speech intelligibility evaluation signals generated
 122 using impulse response (IR) convolution and noise addition were applied to
 123 reproduce eight different noisy environments. In this paper, the term “clean
 124 speech” is used to refer to a signal that is not convoluted with any IR (*i.e.*, dry
 125 source), and to which no noise has been added. The term “degraded speech” is
 126 used to refer to a signal that is convoluted with an IR and to which noise has
 127 been added.

128 The evaluated value of the difference between the degraded speech and the
 129 clean speech of each intelligibility indicator is denoted by d . The intelligibility
 130 index is a value that is monotonically correlated with the subjective evaluation
 131 value of the degraded speech, and represents the reason for varying intelligibility.
 132 Here, it is represented by the estimated intelligibility value $f(d)$ as follows:

$$f(d) = \frac{1}{1 + \exp(b - ad)}, \quad (1)$$

133 where a and b are determined by maximum-likelihood estimation.

134 2.2. STOI

135 STOI [8] is an intelligibility index proposed by Taal et al., which models the
 136 perceptual distortion based on a time-frequency (T-F) model. Figure 1 shows
 137 the process flow of STOI calculation.

138 A T-F model is applied to both clean and degraded speech signals at a
 139 sampling rate of 10 kHz. First, the signals are segmented and Hann-windowed
 140 at 50% overlap steps.

141 The signals are processed to remove the silent frames 40 dB below the max-
 142 imum energy of clean speech. Next, the signals are divided into 15 bands
 143 with central frequencies at one-third octaves from 150 Hz up to approximately
 144 4.3 kHz. The power envelopes of these signals are calculated and used as a T-F
 145 unit. The power envelope $X_j(m)$ from the clean speech x is as follows:

$$X_j(m) = \sqrt{\sum_{k=k_1(j)}^{k_2(j)-1} |\hat{x}(k, m)|^2}, \quad (2)$$

146 where $\hat{x}(k, m)$ is the m -th frame of the k -th DFT bin, j is the number of the
 147 one-third octave band; k_1 and k_2 are the ends of the bandwidth range. A T-
 148 F unit $Y_j(m)$ of the degraded signal y is computed in the same manner, and
 149 therefore we omit its description here.

150 Next, the extraction of the frequency envelopes $\mathbf{x}_{j,m}$ from both clean and
 151 degraded speech signals at an interval N longer than the segmented frames is
 152 performed as follows:

$$\mathbf{x}_{j,m} = [X_j(m - N + 1), X_j(m - N + 2), \dots, X_j(m)], \quad (3)$$

153 where an interval of $N = 30$ (384 ms) is used when calculating the STOI. The
 154 degraded signal vector $y_{j,m}$ is computed in the same manner, and therefore we
 155 omit its description here. The frequency envelope of the degraded signal $y_j(m)$
 156 is then normalized to correct for the global level difference, which does not have
 157 a strong influence upon the intelligibility. The normalized signal $\bar{\mathbf{y}}_{j,m}(n)$ is as
 158 follows:

$$\bar{\mathbf{y}}_{j,m}(n) = \min \left(\frac{\|\mathbf{x}_{j,m}\|}{\|\mathbf{y}_{j,m}\|} \mathbf{y}_{j,m}(n), (1 + 10^{-\beta/20}) x_{j,m}(n) \right), \quad (4)$$

159 where $n \in \{1, \dots, N\}$ and $\|\cdot\|$ is the l_2 norm. In STOI, β is set as -15 dB.

160 Next, equation (5) is used to obtain the correlation coefficients between $\mathbf{x}_{j,m}$
 161 and $\bar{\mathbf{y}}_{j,m}$ in the same band and same frame.

$$d_{j,m} = \frac{(\mathbf{x}_{j,m} - \mu\mathbf{x}_{j,m})^T(\mathbf{y}_{j,m} - \mu\mathbf{y}_{j,m})}{\|\mathbf{x}_{j,m} - \mu\mathbf{x}_{j,m}\| \|\mathbf{y}_{j,m} - \mu\mathbf{y}_{j,m}\|}, \quad (5)$$

162 where μ is the mean value.

163 Finally, the intelligibility index d is calculated as shown below:

$$d = \frac{1}{JM} \sum_{j,m} d_{j,m}, \quad (6)$$

164 where M is averaged over the number of frames, and J is the number of analyzed
 165 bands.

166 Generally, when compared with conventional intelligibility indices, STOI is
 167 considered more robust to speech enhancement because it is based not on the
 168 SNR but on the correlation coefficients between the power envelopes of the
 169 clean and degraded signals. Furthermore, the STOI value correlates well with
 170 the subjective evaluation score when normalization processing in equation (4)
 171 is applied and $N = 30$ is set as the intermediate frame length in equation (3).
 172 STOI has been widely used in a variety of practical research applications (e.g.,
 173 [18, 19]), and extended to a binaural version [20].

174 2.3. SIMI

175 STOI is highly correlated with speech intelligibility, and various improve-
 176 ments to it have been proposed. SIMI [9] is an extension of the STOI developed
 177 by Jensen and Taal; it is based on information theory concepts such as entropy
 178 and mutual information [11]. SIMI assumes that all of the information related
 179 to speech intelligibility is contained in the power envelopes of the clean speech
 180 signal. The SIMI index is the average number of bits of mutual information I
 181 between the clean and degraded power envelopes with a T-F model such as the
 182 STOI. Figure 2 shows the processing flow of SIMI.

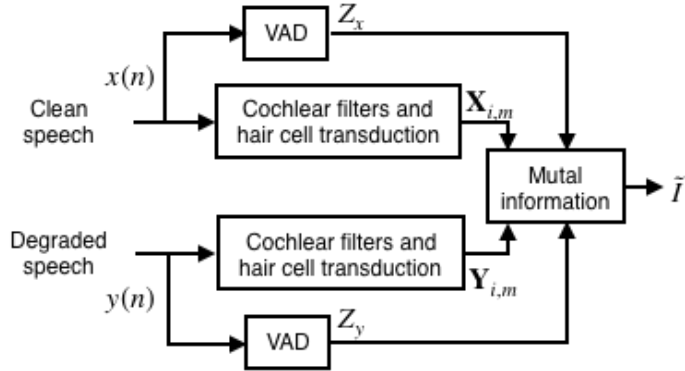


Figure 2: Flowchart of SIMI calculation

183 The power envelopes $\mathbf{x}_{j,m}$ and $\mathbf{y}_{j,m}$ used in SIMI are obtained as shown in
 184 equation (7) in a manner similar to the STOI.

$$\tilde{X}_i(m) = \sqrt{\sum_{k=k_1(i)}^{k_2(i)-1} \left| \sum_{n=0}^{N-1} X(mD+n)\omega(n)e^{-j2\pi kn/N} \right|^2}, \quad (7)$$

185 where the segment length of $N = 256$ is not the same as that for STOI. The
 186 sampling frequency and one-third octave band filters are the same as those for
 187 STOI.

188 The random super-vector χ of the clean speech signal, which is the accumu-
 189 lated critical band power envelope of consecutive frames, is as follows:

$$\chi = [X_1(1)X_2(1)\dots X_L(1)X_2(1)\dots X_L(M)]^T, \quad (8)$$

190 where M is the number of the final frame. The random super-vector ψ of the
 191 degraded speech is obtained in the same way.

192 Next, voice activity detection (VAD) processing is performed to remove low
 193 energy frames from the clean speech signal x and the degraded speech signal
 194 y ; the segments 30 dB or lower than the maximum power of the segment of x
 195 are computed and the lower frames are removed, yielding the active voice index
 196 sequences Z_x and Z_y . The quantity of mutual information I in the sections χ

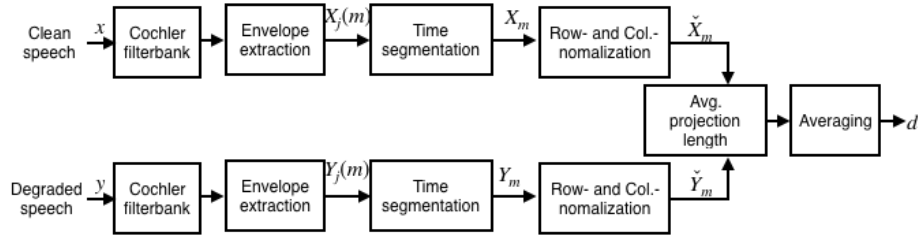


Figure 3: Flowchart of ESTOI calculation

197 and ψ is as follows:

$$\frac{1}{L|Z_x|} I(\chi; \psi) = \frac{1}{L|Z_x|} \sum_{m \in Z_x \cap Z_y} \sum_{i=1}^L I(\mathbf{X}_{j,m}; \mathbf{Y}_{j,m}), \quad (9)$$

198 where L is the maximum of the one-third octave bands. The intelligibility index
 199 of SIMI is $\tilde{I}(\chi; \psi)$, which is defined in equation (10) as the average over the signal
 200 sections as

$$\tilde{I}(\chi; \psi) = \frac{1}{L|Z_x|} \sum_{m \in Z_x \cap Z_y} \sum_{i=1}^L \min(\hat{I}(\mathbf{X}_{j,m}; \mathbf{Y}_{j,m}), I_{\max}), \quad (10)$$

201 where representing the sum of the minimum estimated mutual information
 202 $\hat{I}(\mathbf{X}_{j,m}; \mathbf{Y}_{j,m})$ per 250 ms in evaluation speech signals and the upper limit
 203 $I_{\max} = 0.2$. An upper limit on the amount of mutual information I_{\max} is
 204 established for the purpose of enhancing the correlation with speech intelligibil-
 205 ity.

206 As described above, SIMI is similar to STOI in the way it compares short-
 207 time power envelopes of the clean and degraded speech signals. However, it
 208 differs from STOI in that instead of the Pearson correlation coefficient, it uses
 209 the amount of mutual information based on the information theory.

210 2.4. ESTOI

211 ESTOI is an index proposed by Taal and Jensen, which compares 384-ms-
 212 long spectrograms of the degraded speech and the clean speech signals [10].
 213 Figure 3 shows the process flow of ESTOI. The power envelopes $X_j(m)$ and

214 $Y_j(m)$ are computed through analysis of the signal segmented into one-third oc-
 215 tave bands, as with STOI and SIMI. However, a short-time spectrogram matrix
 216 is then generated, as shown below.

$$X_m = \begin{bmatrix} S_1(m - N + 1) & \dots & S_1(m) \\ \vdots & & \vdots \\ S_j(m - N + 1) & \dots & S_j(m) \end{bmatrix} \quad (11)$$

217 In the same way, S_m is calculated for the degraded speech signal and normalized
 218 using the mean matrix value in each direction to obtain \check{X}_m, \check{Y}_m . This process
 219 is performed every 384 ms as in STOI. Finally, the intelligibility index d is
 220 obtained by averaging the above values, as shown in equation (12).

$$d = \frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N \check{X}_{n,m}^T \check{Y}_{n,m} \quad (12)$$

221 ESTOI is shown to be superior to STOI in terms of intelligibility estimation
 222 performance with degraded speech, and shows good performance for modulated
 223 noise sources [10].

224 2.5. *fwSNRseg*

225 The fwSNRseg [7] intelligibility index proposed by Ma et al. is based on both
 226 time and frequency weights. It splits the SNR of the clean and degraded speech
 227 signals into 30-ms segments and calculates the weighted SNRs for each auditory
 228 critical band. The fwSNRseg is calculated as shown in equation (13).

$$\text{fwSNRseg} = \frac{10}{N} \sum_{m=0}^{M-1} \frac{\sum_{j=1}^K W(j, m) \log_{10} \frac{|x(j, m)|^2}{(|y(j, m)| - |x(j, m)|)^2}}{\sum_{j=1}^K W(j, m)}, \quad (13)$$

229 where m is the segment number, M is the maximum segment number, $W(j, m)$
 230 is the weight of the critical band of the j -th band, and K is the maximum band
 231 number. The dynamic range of fwSNRseg is limited to $[-10, 35]$ dB for better
 232 correlation with the subjective intelligibility score. The number of critical bands
 233 K is set to 25.

234 **3. Subjective intelligibility evaluation**

235 *3.1. Outline of evaluation*

236 In this research, speech intelligibility was subjectively evaluated using the
237 FW07 dataset [17] in the eight noisy environments included in the CENSREC-4
238 corpus [16].

239 *3.2. Word familiarity-controlled word intelligibility test*

240 We used the FW07 dataset [17], which has four levels of word familiarity [21].
241 The FW07 dataset consists of 80 lists of 20 words spoken by two male and two
242 female speakers under each noise condition. In this research, we selected one
243 female speaker from the high-familiarity evaluation speech source lists in the
244 FW07 dataset. The speech intelligibility (SI) using the FW07 dataset was
245 defined as follows:

$$SI = \frac{C}{N}, \quad (14)$$

246 where C is the number of correct answers, and N is the total number of words.

247 An important parameter of speech intelligibility is the relationship between
248 the speech recognition threshold (SRT), which is the speech that can be under-
249 stood 50% of the time, and the physical quantities used for subjective evalu-
250 ation. In this study, subjective evaluation was controlled by the global (long
251 time) SNR under all evaluation conditions. Thus, the global SNR is defined as
252 the intelligibility index d shown in equation (1), and the SRT is calculated as
253 shown in equation (15) using values a and b in equation (1).

$$\text{SRT} = -\frac{b}{a} \quad (15)$$

254 *3.3. Reverberation and background noise environments reproduced by CENSREC-*

255 *4*

256 CENSREC-4 is an evaluation environment simulation set focused on rever-
257 beration, which is used in an automatic speech recognition system under hands

Table 1: IRs and STI values included in CENSREC-4

Condition No.	Condition name	STI values	T_{60} (s)
1	Elevator hall	0.657	0.75
2	In-car (idling)	0.923	0.05
3	Japanese style bath	0.763	0.60
4	Japanese style room	0.779	0.40
5	Living room	0.758	0.65
6	Lounge	0.867	0.50
7	Meeting room	0.836	0.60
8	Office	0.896	0.35

258 free conditions [16]. The CENSREC-4 extra dataset includes background noise
 259 recorded in the same environment as the one used during the measurement of
 260 IR using the time stretched pulse (TSP) method [22] to reproduce the rever-
 261 beration characteristics of the eight environments. The recording environments
 262 are shown in Table 2 together with the other experimental conditions.

263 All IRs in the CENSREC-4 speech signals were presented using a mouth
 264 simulator. For this subjective evaluation, we used the automatic speech recog-
 265 nition system model training subset in the CENSREC-4 extra set. Both the
 266 IRs and background noises recorded a sampling frequency of 16 kHz and 16-bit
 267 quantization.

268 Table 1 lists the IR conditions contained in CENSREC-4. The STI values
 269 of CENSREC-4 were calculated from the IR and reverberation time index of
 270 T_{60} [16]. The eight CENSREC-4 environments listed in this table are the same as
 271 those used in the evaluation and include reverberant conditions. The difference
 272 in reverberant environments is apparent from the difference the STI and T_{60}
 273 values.

274 3.4. *Speech signal generation*

275 The speech signal sources used in the subjective evaluation were selected
276 from the female high-familiarity lists in the FW07 dataset [17]. In this research,
277 we evaluated nine SNR conditions per environmental condition. Therefore, it is
278 necessary to have nine lists (180 words) for each of the eight real environmental
279 conditions, i.e., 72 lists are required by the proposed and reference methods.
280 However, FW07 has only 20 high-familiarity lists; therefore, these 20 lists were
281 used repeatedly. This evaluation flow carries the risk of biasing the results owing
282 to the effect of participants learning words during the evaluation. However,
283 high-familiarity words are likely to have been familiar to the participants from
284 their daily lives; therefore, it was decided to ignore this potential bias. The
285 word lists for each IR and noise condition were assigned randomly. Note that
286 intelligibility indices use the average value of the same signal for analysis, and
287 the same signals were presented to all participants.

288 Furthermore, the FW07 and CENSREC-4 datasets use different sampling
289 rates; we resampled the evaluation signals of the FW07 dataset at 16 kHz to
290 match the sampling frequency of the CENSREC-4 dataset. To compare the
291 environments, it is necessary to ensure that the audio presentation levels are
292 uniform. Therefore, the calibration signal in the FW07 dataset was resampled,
293 IR convolution was performed, and the signal was then adjusted such that the
294 ratio of power to the pre-convoluted calibration sound was constant.

295 3.5. *Subjective evaluation settings*

296 Table 2 shows the subjective evaluation settings. The eight CENSREC-4
297 environments in this table are the same as those used in the evaluation results.
298 Global SNRs between the FW07 speech signals and the CENSREC-4 noise sig-
299 nals were set such that $\text{SNR} = 0$ dB when noise was added to the speech signal
300 at an A-weighted power level identical to the FW07 calibration signal. All sub-
301 jective evaluations took place in a soundproof booth. The ten participants in
302 this evaluation were students (approximately 22 years old) who reported having
303 no hearing abnormalities. All speech signals for evaluation were presented from

Table 2: Subjective evaluation settings

Speaker	female (fto)
Familiarity	high familiarity lists
IR	in Table 1
SNR	−20 to 20 dB (5 dB steps)
Test words	1440 words (72 lists)
Participants	10

304 headphones (Sennheiser; HDA-300) connected to an audio interface (Roland;
305 UA-25EX) and a laptop computer (Windows 7 OS). In each evaluation, speech
306 signals were randomly played back to the participants at a stretch. The par-
307 ticipants repeated the word that they heard to the GUI on a laptop. We made
308 it possible for the participants to set the playback timing of these speech sig-
309 nals in the evaluation as desired in order to allow them to leave the soundproof
310 booth and take breaks during the evaluation. However, only approximately half
311 of each day could be dedicated to experiments, and participants were asked to
312 participate in this evaluation for multiple days. The A-weighted sound pressure
313 level of the speech was adjusted such that the calibration signal of the FW07
314 dataset was presented at 60 dB; the level at which all speech signals were pre-
315 sented remained less than 85 dB when the SNR was set to −20 dB. The sound
316 level was measured as detected by an IEC60318-4 compliant ear simulator (ACO
317 Co., Ltd., Type 2128E) attached to a dummy head (SOUTHERN ACOUSTICS
318 Co., Ltd., SAMURA type 3700). The experiment was conducted with the ap-
319 proval of the Human Research Ethics Review Committee at Muroran Institute
320 of Technology.

321 3.6. Subjective evaluation results

322 Figure 4 shows the results of the subjective evaluation. This figure also
323 shows the results obtained from intelligibility models in equation (1) using the

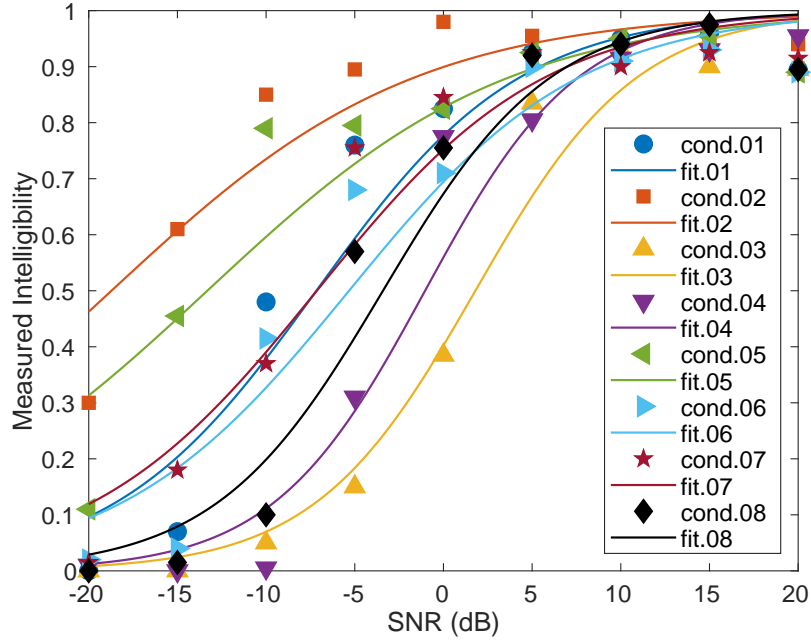


Figure 4: Subjective evaluation results

324 global SNR. These results show that the intelligibility values vary significantly
 325 for the same global SNR depending on the conditions.

326 Table 3 lists the SRTs for each condition. The maximum difference in SRT
 327 is 20.52 dB between cond. 2 and cond 3. Actual speech systems such as PA
 328 systems typically allow only global SNR to be controlled, but it appears that
 329 this by itself is insufficient to control speech intelligibility. In the next section,
 330 we will train a model that uses intelligibility indices to predict the subjective
 331 intelligibility established by these results.

332 The highest STI value of 0.923 for condition 2 in Table 1 exhibited an overall
 333 tendency of general intelligibility. However, the Pearson correlation coefficient
 334 between intelligibility and STI or T_{60} are 0.27 and -0.34 when averaged over
 335 all SNRs. Therefore, STI and T_{60} are not good indicator of the intelligibility in
 336 environments with lower SNR.

Table 3: SRT by conditions

cond.	SRT (dB)	cond.	SRT (dB)
1	-7.17	2	-18.72
3	1.80	4	-1.04
5	-13.31	6	-5.32
7	-7.13	8	-3.41

337 4. Intelligibility estimation & prediction

338 4.1. Intelligibility estimation settings

339 This section describes the intelligibility estimation models, which were trained
340 using four intelligibility indices described in section 2, and explains how we
341 evaluated the prediction accuracy of each model. In this paper, the term “esti-
342 mation” refers to the training of a model of speech intelligibility, and the term
343 “prediction” refers to the use of this model to obtain the predicted values. For
344 each intelligibility index, we computed the scores for all the evaluated words in a
345 list (20 words), and then calculated the arithmetic mean of each of the 20 words
346 under the same condition. We mapped this score to the measured intelligibility
347 obtained by the subjective evaluation in section 3, and the intelligibility estima-
348 tion model in equation (1) was obtained using maximum-likelihood estimation.

349 In this research, following the original proposals for each intelligibility in-
350 dex [7, 8, 9, 10] and other studies, the accuracy of the intelligibility estimation
351 model trained using a degraded speech signal was subjectively evaluated. It
352 was also decided to further evaluate the predictive performance of the objective
353 models in a manner reflective of their actual use. Therefore, the cross-validation
354 (CV) test was performed by training the objective evaluation models under
355 seven of the eight conditions to predict the speech intelligibility under the re-
356 maining unknown condition. This procedure was repeated eight times to cover
357 all noise conditions. We selected the CV test for our prediction performance

358 evaluation because of its ability to evaluate the robustness of the model against
 359 unknown conditions.

360 4.2. Model evaluation methods

361 The Pearson’s correlation coefficient in equation (16) and the RMSE value
 362 in equation (17) were selected to evaluate the prediction performance of the
 363 intelligibility estimation models as follows:

$$r = \frac{\sum_k (f(d) - \mu_{f(d)})(SI_k - \mu_{SI_k})}{\sqrt{\sum_k (f(d) - \mu_{f(d)})^2 \sum_k (SI_k - \mu_{SI_k})^2}}, \quad (16)$$

$$\text{RMSE} = \sqrt{\frac{1}{K} \sum_k (f(d) - SI_k)^2}, \quad (17)$$

364 where both methods compute the predicted intelligibility value of $f(d)$ in equa-
 365 tion (1) and the subjective values evaluated in section 3. In this paper, r_{all} and
 366 RMSE_{all} were computed for models trained under all conditions, whereas r_{CV}
 367 and RMSE_{CV} were computed for the CV tests. The r_{CV} and RMSE_{CV} were
 368 computed as the arithmetic mean over the eight conditions.

369 4.3. Results and discussion

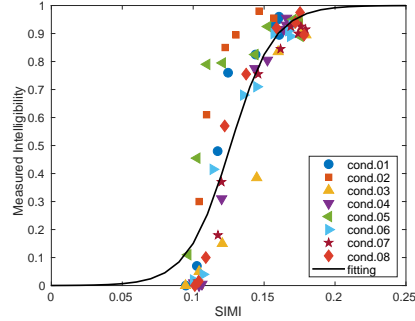
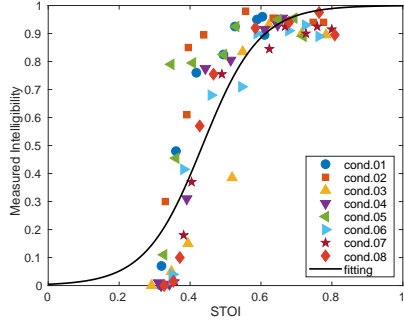
370 Figure 5 shows the mapping of each index to the measured intelligibility and
 371 its modeling function using equation (1). In these figures, the label “cond.”
 372 refers to the corresponding condition in Table 2. These figures show that for
 373 every index, when the measured intelligibility is 0.3 or more, the measured in-
 374 telligibility is higher than the predicted intelligibility value. However, when
 375 the measured intelligibility is less than 0.3, the predicted intelligibility is higher
 376 than the measured value. One reason for these results is that we used only
 377 highly familiar words in order to avoid the effects of learning by the partici-
 378 pants. Consequently, familiarity values cannot be identified by the signals; all
 379 intelligibility indices can only predict an average intelligibility over all familiar-
 380 ity levels. STOI-type indices are computed by comparing the power spectrum
 381 envelope of the clean and degraded speech signals; they cannot account for the

382 effects of familiarity, and should be thought of as approximating the average
383 word familiarity value.

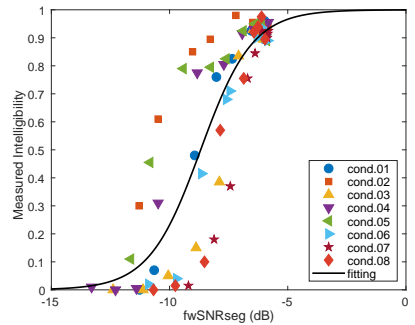
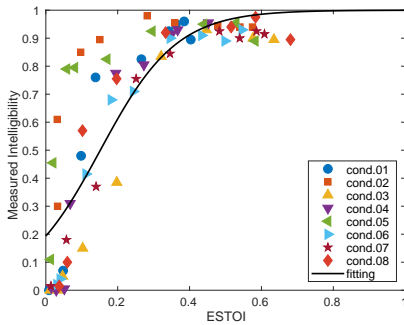
384 We note that PA speech systems used for evacuation broadcasting during
385 a disaster are not designed for use in environments where the intelligibility is
386 extremely low (i.e., where the range of measured intelligibility is below 0.3). In
387 other words, the fact that the predicted intelligibility is somewhat lower than
388 the measured intelligibility should not pose a major problem because it is better
389 to err on the safe side (the actual speech is more intelligible than predicted),
390 considering the practical application of the estimation models to the evaluation
391 of disaster prevention equipment.

392 Table 4 shows the RMSE and correlation coefficient values from each index.
393 This table shows that SIMI had the highest accuracy of all models trained under
394 all conditions. In the CV test results, SIMI had the lowest (best) RMSE_{CV}
395 value, and fwSNRseg had the best correlation coefficient value of r_{CV} . It should
396 be noted that our RMSE_{CV} value for the fwSNRseg index is smaller than that
397 obtained for different speech and noise signals in previous research [13], where
398 the obtained RMSE value significantly exceeded the noise mismatch condition
399 of 0.2. This difference is likely due to the fact that there was less masking
400 of the main speech in this evaluation because none of our eight environments
401 used “babble noise,” which contains speech-like frequency components as the
402 ambient background noise.

403 Here, we discuss the results based on the intelligibility index in reference to
404 SIMI, which showed the best result. In Fig. 5, fwSNRseg roughly shows two
405 noise tendencies unlike that observed with STOI-type measure, which can be
406 considered to result in an increase in the RMSE over SIMI. It is believed that the
407 noise difference becomes conspicuous because it only performs processing over
408 short time segments. On the other hand, STOI and ESTOI in Fig. 5 showed
409 increased RMSE over SIMI because of saturation of the objective intelligibility
410 index value when the measured intelligibility was 0.8 or more. This result sug-
411 gests that the range of mutual information used by SIMI is more robust against
412 minute changes in the saturated range of the measured intelligibility.



(a) Intelligibility mapping and its estimation function using STOI (b) Intelligibility mapping and its estimation function using SIMI



(c) Intelligibility mapping and its estimation function using ESTOI (d) Intelligibility mapping and its estimation function using fwSNRseg

Figure 5: Measured intelligibility and its modeling functions.

413 Figure 6 shows the relationship between the measured intelligibility and
 414 predicted intelligibility in the CV experiment. These results show that the
 415 fwSNRseg model generates many samples that deviate significantly from the
 416 diagonal line. The other indices (STOI-type) are closer to the diagonal line,
 417 with the measured intelligibility tending to be higher than the predicted value.
 418 The fwSNRseg index also differs from the other indices in that its predictions
 419 are not clustered near 0.2 when the measured intelligibility value is 0. This
 420 behavior explains why the SIMI index had the best $RMSE_{CV}$ value of 0.160 in

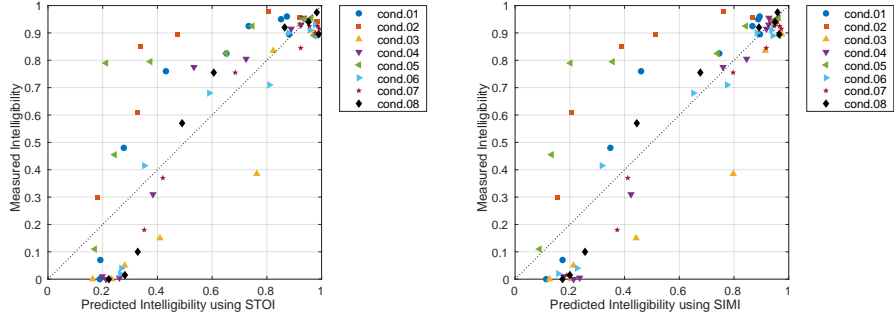
Table 4: Intelligibility prediction results; the best results are shown in bold.

Index	r_{all}	r_{CV}	RMSE _{all}	RMSE _{CV}
STOI	0.878	0.908	0.175	0.181
SIMI	0.901	0.934	0.158	0.160
ESTOI	0.873	0.910	0.178	0.183
fwSNRseg	0.875	0.941	0.176	0.184

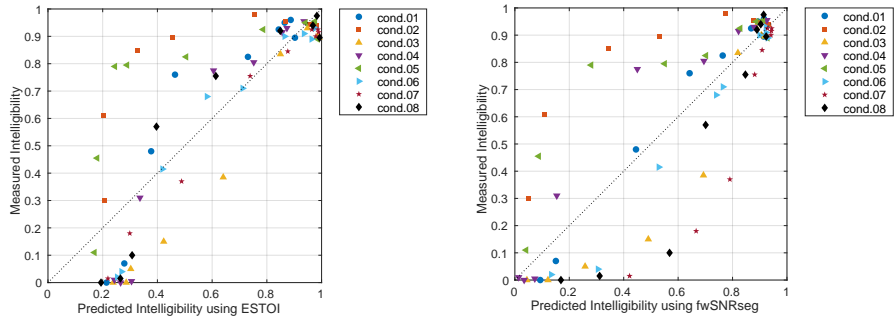
421 spite of fwSNRseg having the best r_{CV} value of 0.941. From the perspective of
 422 practical use, the fwSNRseg index would appear to be more difficult to apply
 423 owing to its large overall variability, given that the measured intelligibility in
 424 the outdoor sound field will typically fall near the center of the intelligibility
 425 values.

426 Considering the above factors comprehensively, the best index for prediction
 427 of speech intelligibility in a noisy environment would appear to be SIMI. This
 428 conclusion is consistent with the performance evaluation reported by Jensen and
 429 Taal in their paper introducing SIMI [9], which found it to be superior to STOI
 430 at estimating the intelligibility of speech in a noisy environment.

431 However, our research is not concerned with noise reduction. We conclude
 432 that among the existing measurement standards, SIMI is the best speech intel-
 433 ligibility index to choose for speech systems that broadcast unmodified speech
 434 such as a PA system. The reason for the superiority of SIMI may be explained
 435 by the fact that it has been optimized to assess the intelligibility of noise added
 436 speech rather than noise-suppressed speech through parameters such as the VAD
 437 (30 dB), analysis interval (250 ms), and upper limit on the amount of mutual
 438 information I_{max} , which differ from the corresponding settings in STOI and ES-
 439 TOI. In the future, the optimal parameter settings specific to Japanese speech
 440 intelligibility prediction in noisy environments should be investigated.



(a) Intelligibility prediction results using STOI (b) Intelligibility prediction results using SIMI



(c) Intelligibility prediction results using ESTOI (d) Intelligibility-prediction results using fwSNRseg

Figure 6: Relationship between measured intelligibility and predicted intelligibility in the CV experiment

441 **5. Conclusions**

442 In this study, we modeled Japanese speech intelligibility based on four in-
 443 telligibility indices. The models were trained and their accuracies in predicting
 444 the measured speech intelligibility using the FW07 speech dataset under the
 445 eight noisy environments included in the CENSREC-4 dataset were evaluated.
 446 We compared the STOI, SIMI, ESTOI, and fwSNRseg indices. The results of
 447 our CV experiment showed that SIMI, which is based on the amount of mutual
 448 information in the clean and degraded speech signals, gave the most accurate in-

449 telligibility index, as evaluated by $RMSE_{CV}$ and its correlation coefficient. Our
450 plans for future works are to optimize the internal parameters of SIMI and to
451 develop a system to feed SIMI's predicted intelligibility directly into the speech
452 system for feedback.

453 **Acknowledgments**

454 This work was supported in part by JSPS KAKENHI Grant Number No.
455 16K21584 and the Cooperative Research Project of the Research Institute of
456 Electrical Communication, Tohoku University (H29/A18).

457 **References**

- 458 [1] N. R. French, J. C. Steinberg, Factors Governing the Intelligibility of Speech
459 Sounds, *The Journal of the Acoustical Society of America* 19 (1) (1947) 90–
460 119. doi:10.1121/1.1916407.
- 461 [2] K. D. Kryter, Methods for the Calculation and Use of the Articulation
462 index, *The Journal of the Acoustical Society of America* 34 (11) (1962)
463 1689–1697. doi:10.1121/1.1909094.
- 464 [3] American National Standards Institute, N.Y., USA, ANSI S3.5, American
465 National Standard Methods for the Calculation of the Articulation Index
466 (1969).
- 467 [4] American National Standards Institute, N.Y., USA, ANSI S3.5, Methods
468 for the Calculation of the Speech Intelligibility Index (1995).
- 469 [5] H. J. M. Steeneken, T. Houtgast, A physical method for measuring speech-
470 transmission quality, *The Journal of the Acoustical Society of America* 67
471 (1980) 318–326. doi:10.1121/1.384464.
- 472 [6] International Electrotechnical Commission, Geneva, Switzerland, IEC
473 60268-16, Sound system equipment-Part 16 : Objective rating of speech
474 intelligibility by speech transmission index (2003).

- 475 [7] J. Ma, Y. Hu, P. C. Loizou, Objective measures for predicting speech intel-
476 ligibility in noisy conditions based on new band-importance functions, *The*
477 *Journal of the Acoustical Society of America* 125 (5) (2009) 3387–3405.
478 doi:10.1121/1.3097493.
- 479 [8] C. H. Taal, R. C. Hendriks, R. Heusdens, J. Jensen, An algorithm for intelli-
480 gibility prediction of time-frequency weighted noisy speech, *IEEE Transac-*
481 *tions on Audio, Speech, and Language Processing* 19 (7) (2011) 2125–2136.
482 doi:10.1109/TASL.2011.2114881.
- 483 [9] J. Jensen, C. H. Taal, Speech intelligibility prediction based on mutual
484 information, *IEEE/ACM Transactions on Audio, Speech, and Language*
485 *Processing* 22 (2) (2014) 430–440. doi:10.1109/TASLP.2013.2295914.
- 486 [10] J. Jensen, C. H. Taal, An algorithm for predicting the intelligibility of
487 speech masked by modulated noise maskers, *IEEE/ACM Transactions*
488 *on Audio, Speech, and Language Processing* 24 (11) (2016) 2009–2022.
489 doi:10.1109/TASLP.2016.2585878.
- 490 [11] T. M. Cover, J. A. Thomas, *Elements of Information Theory* (Wiley Series
491 in Telecommunications and Signal Processing), Wiley-Interscience, New
492 York, NY, USA, 2006.
- 493 [12] J. Li, F. Chen, M. Akagi, Y. Yan, Comparative investigation of objective
494 speech intelligibility prediction measures for noise-reduced signals in Man-
495 darin and Japanese, in: *Proc. INTERSPEECH 2013*, 2013, pp. 1184–1187.
- 496 [13] K. Kondo, Estimation of speech intelligibility using objec-
497 tive measures, *Applied Acoustics* 74 (1) (2013) 63 – 70.
498 doi:https://doi.org/10.1016/j.apacoust.2012.06.009.
- 499 [14] T. Sakano, Y. Kobayashi, K. Kondo, A Speech Intelligibility
500 Estimation Method Using a Non-reference Feature Set, *IEICE*
501 *Transactions on Information and Systems* 98-D (1) (2015) 21–28.
502 doi:10.1587/transinf.2014MUP0004.

- 503 [15] K. Nakazawa, K. Kondo, De-reverberation using DNN for Non-Reference
504 Reverberant Speech Intelligibility Estimation, in: Proc. IEEE 7th Global
505 Conference on Consumer Electronics (GCCE 2018), 2018, pp. 2378–8143.
506 doi:10.1109/GCCE.2018.8574754.
- 507 [16] T. Fukumori, T. Nishiura, M. Nakayama, Y. Denda, N. Kitaoka, T. Ya-
508 mada, K. Yamamoto, S. Tsuge, M. Fujimoto, T. Takiguchi, C. Miyajima,
509 S. Tamura, T. Ogawa, S. Matsuda, S. Kuroiwa, K. Takeda, S. Nakamura,
510 Censrec-4: An evaluation framework for distant-talking speech recognition
511 in reverberant environments, *Acoustical Science and Technology* 32 (5)
512 (2011) 201–210. doi:10.1250/ast.32.201.
- 513 [17] S. Sakamoto, T. Yoshikawa, S. Amano, Y. Suzuki, T. Kondo, New 20-word
514 lists for word intelligibility test in japanese, in: Proc. INTERSPEECH
515 2006, ISCA, 2006, pp. 2158–2161.
- 516 [18] D. Yun, H. Lee, S. H. Choi, A deep learning-based approach to
517 non-intrusive objective speech intelligibility estimation, *IEICE Trans-*
518 *actions on Information and Systems* E101.D (4) (2018) 1207–1208.
519 doi:10.1587/transinf.2017EDL8225.
- 520 [19] Y. Koizumi, K. Niwa, Y. Hioka, K. Kobayashi, Y. Haneda, Dnn-based
521 source enhancement to increase objective sound quality assessment score,
522 *IEEE/ACM Transactions on Audio, Speech, and Language Processing*
523 26 (10) (2018) 1780–1792. doi:10.1109/TASLP.2018.2842156.
- 524 [20] A. H. Andersen, J. M. de Haan, Z.-H. Tan, J. Jensen, Refinement and
525 validation of the binaural short time objective intelligibility measure for
526 spatially diverse conditions, *Speech Communication* 102 (2018) 1 – 13.
527 doi:https://doi.org/10.1016/j.specom.2018.06.001.
- 528 [21] S. Amano, T. Kondo, K. Kato, Familiarity effect on spoken word recogni-
529 tion in japanese, in: Proc. 14th International Congress of Phonetic Science,
530 Vol. 2, 1999, pp. 873–876.

531 [22] Y. Suzuki, F. Asano, H. Kim, T. Sone, An optimum computer - generated
532 pulse signal suitable for the measurement of very long impulse responses,
533 The Journal of the Acoustical Society of America 97 (2) (1995) 1119–1123.
534 doi:10.1121/1.412224.