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On Temporomandibular Joint Sound Signal Analysis Using ICA

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1. Introduction

The Temporomandibular Joint (TMJ) is the joint which connects the lower jaw, called the mandible, to the temporal bone at the side of the head. The joint is very important with regard to speech, mastication and swallowing. Any problem that prevents this system from *functioning* properly may result in temporomandibular joint disorder (TMD). Symptoms include pain, limited movement of the jaw, radiating pain in the face, neck or shoulders, painful clicking, popping or grating sounds in the jaw joint during opening and/or closing of the mouth. TMD being the most common non-dental related chronic source of oral-facial pain(Gray et al., 1995)(Pankhurst C. L, 1997), affects over 75% of the United States population(Berman et al., 2006). TMJ sounds during jaw motion are important indication of dysfunction and are closely correlated with the joint pathology(Widmalm et al., 1992). The TMJ sounds are routinely recorded by auscultation and noted in dental examination protocols. However, stethoscopic auscultation is very subjective and difficult to document. The interpretations of the sounds often vary among different doctors. Early detection of TMD, before irreversible gross erosive changes take place, is extremely important.

Electronic recording of TMJ sounds therefore offers some advantages over stethoscopic auscultation recording by allowing the clinician to store the sound for further analysis and future reference. Secondly, the recording of TMJ sounds is also an objective and quantitative record of the TMJ sounds during the changes in joint pathology. The most important advantage is that electronic recording allows the use of advanced signal processing techniques to the automatic classification of the sounds. A cheap, efficient and reliable diagnostic tool for early detection of TMD can be developed using TMJ sounds recorded with a pair of microphones placed at the openings of the auditory canals. The analysis of these recorded TMJ vibrations offers a powerful non-invasive alternative to the old clinical methods such as auscultation and radiation.

In early studies, the temporal waveforms and power spectra of TMJ sounds were analyzed(Widmalm et al., 1991) to characterize signals based on their time behavior or their energy distribution over a frequency range. However, such approaches are not sufficient to

fully characterize non-stationary signals like TMJ sounds. In other words, for non-stationary signals like TMJ vibrations, it is required to know how the frequency components of the signal change with time. This can be achieved by obtaining the distribution of signal energy over the TF plane (Cohen L., 1995). Several joint time-frequency analysis methods have then been applied to the analysis and classification of TMJ vibrations into different classes based on their time-frequency reduced interference distribution (RID) (Widmalm & Widmalm, 1996) (Akan et al., 2000). According to TF analysis, four distinct classes of defective TMJ sounds are defined: click, click with crepitation, soft crepitation, and hard crepitation (Watt, 1980). Here, clicks are identified as high amplitude peaks of very short duration, and crepitations are signals with multiple peaks of various amplitude and longer duration as well as a wide frequency range.

In this chapter, instead of discussing the classification of TMJ sounds into various types based on their TF characteristics, we address the problem of source separation of the stereo recordings of TMJ sounds. Statistical correlations between different type of sounds and the joint pathology have been explored by applying ICA based methods to present a potential diagnostic tool for temporomandibular joint disorder.

The chapter outline is as follows: The details for data acquisition are elaborated in Section 2, followed by the problem definition and the possible contribution of the independent component analysis (ICA) based approach. The proposed signal mixing and propagation models are then proposed in Section 3, with the theoretical background of ICA and the proposed ICA based solutions described in Sections 4 to 6. The illustrative results of the present method on both simulated and real TMJ signals are compared with other existing source separation methods in Section 7. The performance of the method has been further evaluated quantitatively in Section 8. Lastly, the chapter summary and discussion are presented in Section 9.

2. Data acquisition

The auditory canal is an ideal location for the non-invasive sensor (microphone) to come as close to the joint as possible. The microphones were held in place by earplugs made of a kneadable polysiloxane impression material (called the Reprosil putty and produced by Dentsply). A hole was punched through each earplug to hold the microphone in place and to reduce the interference of ambient noise in the recordings.

In this study, the TMJ sounds were recorded on a Digital Audio Tape (DAT) recorder. During recording session, the necessary equipments are two Sony ECM-77-B electret condenser microphones, Krohn-Hite 3944 multi-channel analog filter and TEAC RD-145T or TASCAM DA-P1 DAT recorder. The microphones have a frequency response ranges from 40–20,000 Hz and omni-directional. It acts as a transducer to capture the TMJ sounds. The signals were then passed through a lowpass filter to prevent aliasing effect of the digital signal. A Butterworth filter with a cut-off frequency of 20 KHz and attenuation slope of 24 dB/octave was set at the analog filter. There is an option to set the gain at the filter to boost up the energy level of the signal. The option was turned on when the TMJ sounds were too soft and the signals from the microphones were amplified to make full use of the dynamic range of the DAT recorder. Finally, the signals from the analog filter were sampled in the DAT recorder at the rate of 48 KHz and data were saved on a disc.

3. Problems and solution: The role of ICA

One common and major problem in both stethoscopic auscultation and digital recording is that the sound originating from one side will propagate to the other side, leading to misdiagnosis in some cases. It is shown in Fig. 1(a) that short duration TMJ sounds (less than 10ms) are frequently recorded in both channels very close in time. When the two channels show similar waveforms, with one lagging and attenuated to some degree, it can be concluded that the lagging signal is in fact the propagated version of the other signal (Widmalm et al., 1997).

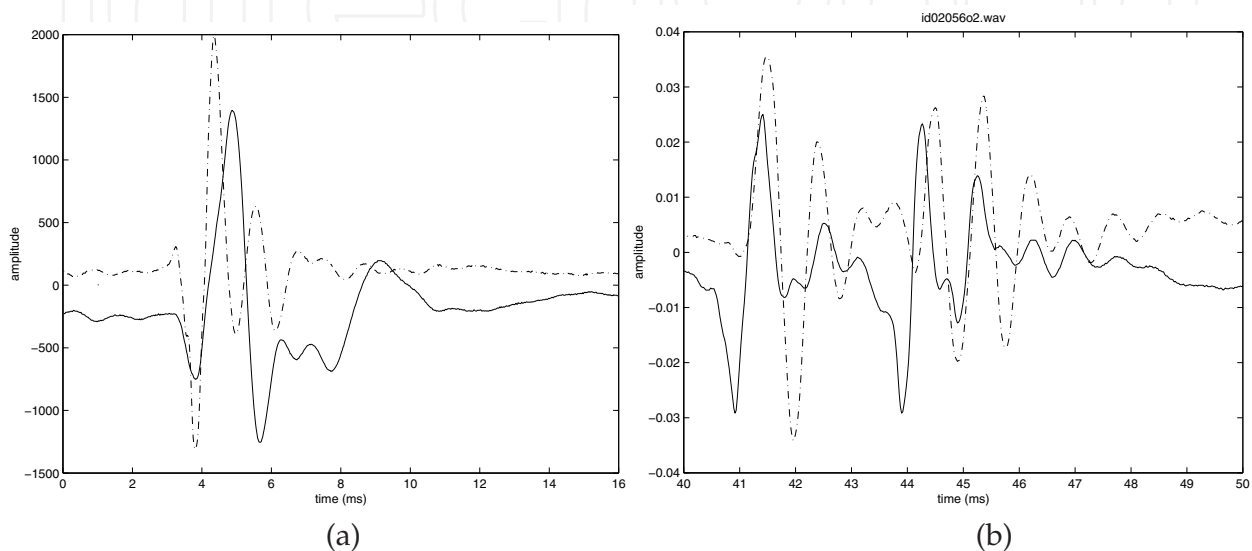


Fig. 1. TMJ sounds of two channels.

This observation is very important. It means that a sound heard at auscultation on one side may have actually come from the other TMJ. This has great clinical significance because it is necessary to know the true source of the recorded sound, for example in diagnosing so called disk displacement with reduction (Widmalm et al., 1997). The TMJ sounds can be classified into two major classes: clicks and crepitations. A click is a distinct sound, of very limited duration, with a clear beginning and end. As the name suggests, it sounds like a “click”. A crepitation has a longer duration. It sounds like a series of short but rapidly repeating sounds that occur close in time. Sometimes, it is described as “grinding of snow” or “sand falling”. The duration of a click is very short (usually less than 10ms). It is possible to differentiate between the source and the propagated sound without much difficulty. This is due to the short delay (about 0.2ms) and the difference in amplitude between the signals of the two channels, especially if one TMJ is silent. However, it is sometimes very difficult to tell which is the source signals from the recordings. In Fig. 1(b), it seems that the dashed line is the source if we simply look at the amplitude. On the other hand, it might seem that the solid line is the source if we look at the time (it comes first). ICA could have vital role to solve this problem since both the sources (sounds from both TMJ) and the mixing process (the transfer function of the human head, bone and tissue) are unknown. If ICA is used, one output should be the original signal and the other channel should be silent with very low amplitude noise picked up by the microphone. Then it is very easy to tell which channel is the original sound. Furthermore, in the case of crepitation sounds, the duration of the signal is longer, and further complicated by the fact that both sides may crepitate at the same time. The ICA is then proposed as a means to recover the original sound for each channel.

4. Mixing model of TMJ sound signals

In this chapter, the study is not limited to patients with only one defective TMD joint. We thus consider the TMJ sounds recorded simultaneously from both sides of human head as a mixture of crepitations/clicks from the TMD affected joint and the noise produced by the other healthy TMJ or another crepitation/click. Instead of regarding the 'echo' recorded on the contra (i.e. opposite) side of the TMD joint as the lagged version of the TMD source (Widmalm et al., 2002), we consider here the possibility that this echo as a mixture of the TMD sources. Mathematically, the mixing model of the observed TMJ sound measurements is represented as

$$x_i(t) = \sum_{j=1}^2 h_{ij}s_j(t - \delta_{ij}) + n_i(t) \quad (1)$$

with s_j being the j th source and x_i as the i th TMJ mixture signal with $i = 1, 2$. The additive white Gaussian noise at discrete time t is denoted by $n_i(t)$. Also, the attenuation coefficients, as well as the time delays associated with the transmission path between the j th source and the i th sensor (i.e. microphone) are denoted by h_{ij} and δ_{ij} , respectively.

Fig. 2 shows how the TMJ sounds are mixed. Sounds originating from a TMJ are picked up by the microphone in the auditory canal immediately behind the joint and also by the microphone in the other auditory canal as the sound travels through the human head.

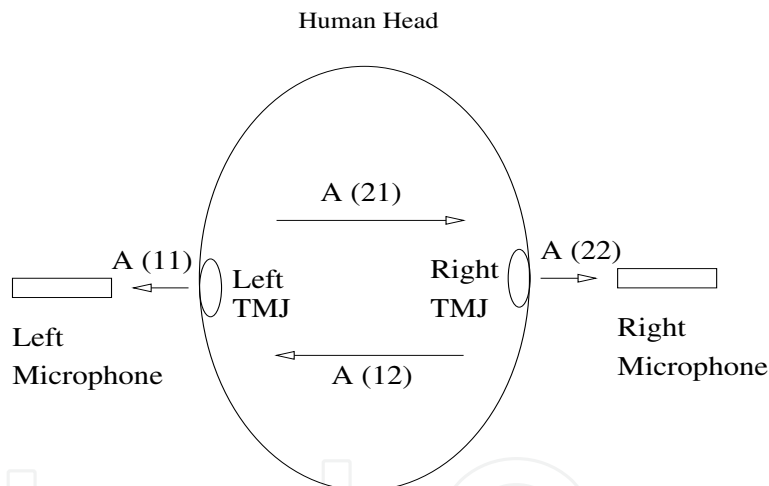


Fig. 2. Mixing model of TMJ sounds (A_{ij} refers to the acoustic path between the $j = 1$ (i.e. left side of human head) source and the $i = 2$ (right side of the human head) sensor).

The mixing matrix \mathbf{H} could therefore be defined as below with z^{-1} indicating unit delay:

$$\mathbf{H} = \begin{pmatrix} h_{11}z^{-\delta_{11}} & h_{12}z^{-\delta_{12}} \\ h_{21}z^{-\delta_{21}} & h_{22}z^{-\delta_{22}} \end{pmatrix} \quad (2)$$

Please note that the time delay δ is not necessarily to be integer due to the uncertainty in sound transmission time in tissues.

The independency of the TMJ sound sources on both sides of the head might not hold as both joints operate synchronously during the opening and closing of mouth. Therefore, unlike the convolutive mixing model assumed in our previous paper (Guo et al., 1999), the instantaneous mixing model presented here does not depend on the assumption of statistical independence

of the sources. In this work, the main assumptions made include the non-stationarity of all the source signals as well as anechoic head model. Here, the anechoic model is assumed due to the facts that:

1. TMJ sound made by the opposite side of the TMD joint has been reported as a delayed version of its ipsi(Widmalm et al., 2002).
2. The TMJ sounds has a wide bandwidth of [20, 3200]Hz. While it travels across the head, the high frequency components (>1200Hz) have been severely attenuated(O'Brien et al., 2005).

Single effective acoustic path from one side of the head to the other side is thus assumed. Also, the mixing model in Eq. (1) holds with mixing matrix presented in Eq. (2). However, due to the wide bandwidth of crepitation, source TMJ signals are not necessarily to be sparse in the time-frequency domain. This gives the proposed ICA based method better robustness as compared to the blind source separation algorithm proposed in(Took et al., 2008).

5. Theoretical background of ICA

There are three basic and intuitive principles for estimating the model of independent component analysis.

1) ICA by minimization of mutual information

This is based on information-theoretic concept, i.e. information maximization (InfoMax) as briefly explained here.

The differential entropy H of a random vector y with density $p(y)$ is defined as (Hyvärinen, 1999):

$$H(y) = - \int p(y) \log p(y) dy \quad (3)$$

Basically, the mutual information I between m (scalar) random variables $y_i, i = 1 \dots m$ is defined as follows:

$$I(y_1, y_2, \dots, y_m) = \sum_{i=1}^m H(y_i) - H(y) \quad (4)$$

The mutual information is $I(y_1, y_2) = \sum_{i=1}^2 H(y_i) - H(y_1, y_2)$, where $\sum_{i=1}^2 H(y_i)$ is marginal entropy and $H(y_1, y_2)$ is joint entropy. The mutual information is a natural measure of the dependence between random variables. It is always nonnegative, and zero if and only if the variables are statistically independent. Therefore, we can use mutual information as the criterion for finding the ICA representation, i.e. to make the output "decorrelated". In any case, minimization of mutual information can be interpreted as giving the maximally independent components(Hyvärinen, 1999).

2) ICA by maximization of non-Gaussianity

Non-Gaussianity is actually most important in ICA estimation. In classic statistical theory, random variables are assumed to have Gaussian distributions. So we start by motivating the maximization of Non-Gaussianity by the central limit theorem. It has important consequences in independent component analysis and blind source separation. Even for a small number of sources the distribution of the mixture is usually close to Gaussian. We can simply explained the concept as follows:

Let us assume that the data vector x is distributed according to the ICA data model: $x = Hs$ is a mixture of independent source components s and H is the unknown full rank ($n \times m$) mixing matrix for m mixed signals and n independent source components. Estimating the independent components can be accomplished by finding the right linear combinations of the mixture variables. We can invert the mixing model in vector form as: $s = H^{-1}x$, so the linear combination of x_i . In other words, we can denote this by $y = b^T x = \sum_{i=1}^m b_i x_i$. We could take b as a vector that maximizes the Non-Gaussianity of $b^T x$. This means that $y = b^T x$ equals one of the independent components. Therefore, maximizing the Non-Gaussianity of $b^T x$ gives us one of the independent components (Hyvärinen, 1999). To find several independent components, we need to find all these local maxima. This is not difficult, because the different independent components are uncorrelated. We can always constrain the search to the space that gives estimates uncorrelated with the previous ones (Hyvärinen, 2004).

3) ICA by maximization of likelihood

Maximization of likelihood is one of the popular approaches to estimate the independent components analysis model. Maximum likelihood (ML) estimator assumes that the unknown parameters are constants if there is no prior information available on them. It usually applies to large numbers of samples. One interpretation of ML estimation is calculating parameter values as estimates that give the highest probability for the observations. There are two algorithms to perform the maximum likelihood estimation:

- Gradient algorithm: this is the algorithms for maximizing likelihood obtained by the gradient based method (Hyvärinen, 1999).
- Fast fixed-point algorithm (Ella, 2000): the basic principle is to maximize the measures of Non-Gaussianity used for ICA estimation. Actually, the FastICA algorithm (gradient-based algorithm but converge very fast and reliably) can be directly applied to maximization of the likelihood.

6. The proposed ICA based TMJ analysis method

The proposed ICA based TMJ analysis method is based on the following considerations: i) asymmetric mixing, ii) non-sparse source conditions. Based on the above criterion we consider to apply the ICA technique based on information maximization as introduced above in Section 5 for the analysis of TMJ signals. We therefore propose an improved Infomax method based on its robustness against noise and general mixing properties. The present method has an adaptive contrast function (i.e. adaptive log-sigmoidal function) together with non-causal filters over the conventional Infomax method in Bell & Sejnowski (1995); Torkkola (1996) to get better performance for a pair of TMJ sources.

The nonlinear function, f , must be a monotonically increasing or decreasing function. In this paper, the nonlinear function proposed is defined as

$$y = f(u; b, m) = [1/(1 + e^{-bu})]^m. \quad (5)$$

Maximizing the output information can be then achieved by minimizing the mutual information between the outputs y_1 and y_2 of the above adaptive f function. In Eq. (5) the adaptation in the slope parameter b is equivalent to adaptive learning rate during our iterative process. This let us perform the iteration with a small learning rate followed by larger learning

rate as the iteration proceeds. On the other hand, during iteration the exponent parameter m is kept as $m = 1$ in our case in order to make sure that the important 'click' signals are not skewed.

Moreover, algorithm in (Torkkola, 1996) performs well when there is stable inverse of the direct channel(i.e. ipsi side) which is not always feasible in real case. In the separation of TMJ sound signals, the direct channel is the path from the source (TMJ) through the head tissue to the skull bone, then to the air in the auditory canal directly behind the TMJ and finally to the ipsi microphone. The corresponding acoustic response would come from a very complex process, for which it is not guaranteed that there will a stable inverse for this transfer function.

However, even if a filter does not have a stable causal inverse, there still exists a stable non-causal inverse. Therefore, the algorithm of Torkkola can be modified and used even though there is no stable (causal) inverse filter for the direct channel. The relationships between the signals are now becomes:

$$\begin{aligned} u_1(t) &= \sum_{k=-M}^M w_k^{11} x_1(t-k) + \sum_{k=-M}^M w_k^{12} u_2(t-k) \\ u_2(t) &= \sum_{k=-M}^M w_k^{22} x_2(t-k) + \sum_{k=-M}^M w_k^{21} u_1(t-k) \end{aligned} \quad (6)$$

where M (even) is half of the (total filter length-1) and the zero lag of the filter is at $(M + 1)$. In (6) there exist an initialization problem regarding filtering. To calculate the value of $u_1(t)$, the values of $u_2(t), u_2(t+1), \dots, u_2(t+M)$ are required which are not initially available. Since learning is an iteration process, we have used some pre-assigned values to solve this filter initialization problem. For example, the value of $x_2(t)$ is used for $u_2(t)$ at the first iteration. The new values generated at the first iteration are then used for the second iteration. This process is repeated until its convergence to certain values. For each iteration, the value of the parameter b in the corresponding f function is updated based on its empirical initial/end values and total number of iterations. The expressions of b in Eq. (5) at the p^{th} iteration is then defined as:

$$b(p) = b_o + (p - 1)\Delta b \quad (7)$$

where $p = 1, 2, \dots, iter$ and $iter$ is the total number of iterations. The Δb are obtained as $\Delta b = (b_e - b_o)/iter$ with $b \in [b_o, b_e]$. To avoid the saturation problem of the adaptive log-sigmoid function and for better use of nonlinearity, we restrict the b parameter within the interval $[1, 10]$.

The derivative of the learning rule can follow the same procedure as in Torkkola (1996). According to (6), only the unmixing coefficients of W_{12} and W_{21} have to be learned. The learning rule is the same in notation but different in nature because the values of k have changed:

$$\Delta w_k^{ij} \propto (1 - 2y_i)u_j(t-k) \quad (8)$$

where $k = -M, -M + 1, \dots, M$.

7. Results

7.1 Illustrative results on simulated signals

Simulated click signals are generated following the definition present in (Akan et al., 2000) as an impulse with very short duration (20 ms) and high amplitude peaks. Since normal TMJ is assumed to produce no sound, we have used a sine wave at 20 Hz with 1/10 click amplitude to

represent normal TMJ sound. Fig. 3(a) shows an example simulation of TMJ sources with their corresponding mixtures captured by the sensors being simulated and illustrated in Fig. 3(b). The illustrated plots are generated to describe the signals being captured by sensors placed in each auditory canal of a patient with right TMD joint producing unilateral clicking. No power attenuation and delay for transmissions between sources and sensors on the same side of the head have thus been assumed.

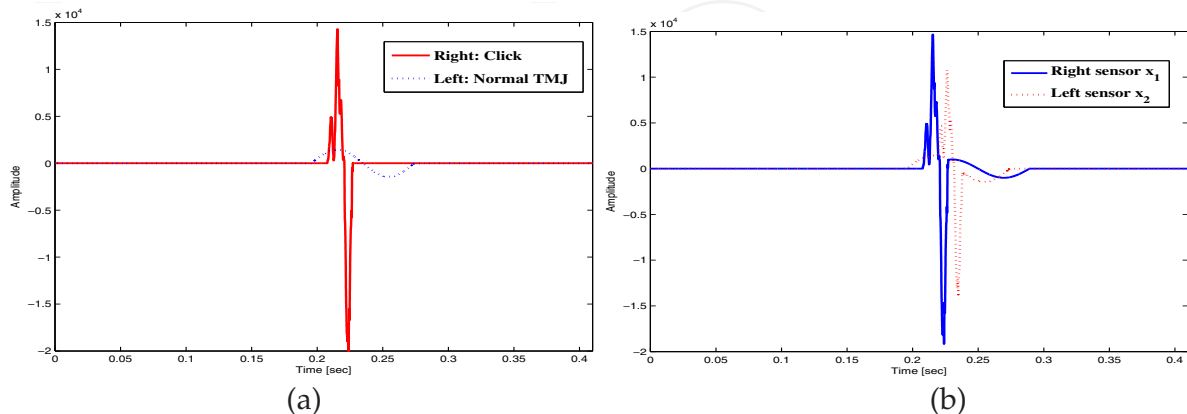


Fig. 3. Simulated (a) TMJ sources (click and normal TMJ sounds) and (b) the corresponding mixed signals.

The simulated mixing model parameters are therefore set as: $h_{11} = h_{22} = 1$ and $\delta_{11} = \delta_{22} = 0$. Also, a time delay of 1 ms between the two TMJ sounds has been observed in Fig. 6 which falls within the range of 0.2 to 1.2 ms reported in (Widmalm et al., 2002). Thus, $\delta_{12} = 1.1$ ms and $\delta_{21} = 1.5$ ms are set based on the above observations and the fact that signal with lower frequency travels slower than that of higher frequency. According to (Widmalm et al., 2003), frequencies greater than 1200 Hz of the ipsi TMJ sound were found to be severely attenuated when it propagates to the contra side, $h_{12} = h_{21}$ is thus set to have an impulse response of a lowpass filter with stopband at 1200 Hz and passband attenuation of 3 dB. The noise on both sides is considered as $n_1 = n_2 = 0$ for simplicity purpose. The illustrative results of ICA for the signals in Fig. 3 are presented in Figs. 4(a)-(b).

7.2 Illustrative results on real TMJ recordings

Fig. 5 shows a typical recording of TMJ crepitation sounds from the two microphones. Each recording is a mixture of the two TMJ sources. The sampling rate of the recorded TMJ signals is 48 KHz.

If we zoom in on Fig. 5 near 0.045s, the signals are shown in Fig. 6(a) for both channels (solid line for channel one and dashed line for channel two). It is difficult to tell how much of the signal in each channel comes from the ipsi (same side) TMJ and how much comes from the contra (opposite) TMJ (Widmalm et al., 1997). If we look at the signals near 0.35s (Fig. 6(b)), it is even more difficult to differentiate the source from the propagated component because the signals are almost 180° out of phase. It is almost impossible to determine the short time delay and difference in amplitudes between the two signals.

The results of ICA for the signals in Fig. 5 are presented in Fig. 7. In order to see the important role of ICA, let us look at the signals near 0.35s (Fig. 8). It clearly shows that the signal only comes from the first channel (solid line) and the second channel (dashed line) is basically

silent. From Fig. 7, it is also clear that the source is now coming from channel two at the time near 0.045s.

8. Performance evaluation

For comparison purposes, the source estimates of Infomax(Guo et al., 1999), FastICA(Hyvärinen et al, 2000), and the original DUET(Widmalm et al., 2002) approach are also included in the simulation studies. The un-mixing filter length was set to be 161 for the Infomax approach, and the DUET approach assumes the W -disjoint orthogonality of the source signals, where at most one source is dominating over any particular TF interval. The illustrative results of the extracted sources from real TMJ recordings by these three reference methods are depicted in Fig 7. The source separation results on simulated mixture of click and normal TMJ sounds using various methods are denoted in Fig 4. The signal in the left column is evidently the click source, while the reduced traces of those prominent peaks in signal from right column suggests that it is in fact the sound produced by the healthy/normal joint. Although the FastICA method is able to estimate the normal source with the minimum

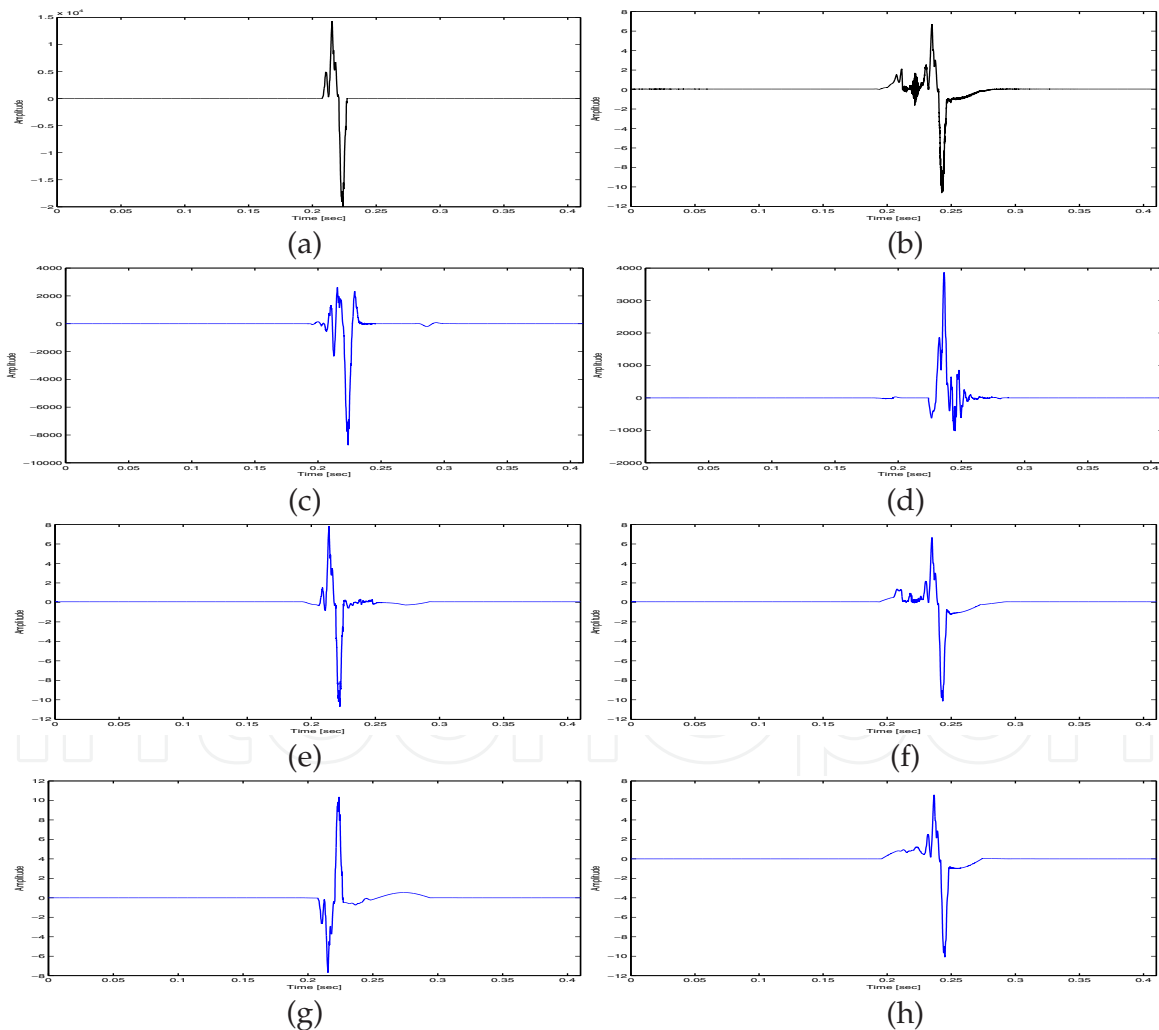


Fig. 4. The results of (a-b) the proposed ICA based source extraction method; (c-d) DUET method in (Widmalm et al., 2002); (e-f) Infomax approach in (Guo et al., 1999); (g-h) FastICA approach in (Hyvärinen et al, 2000) on simulated TMJ mixtures in Fig. 3.

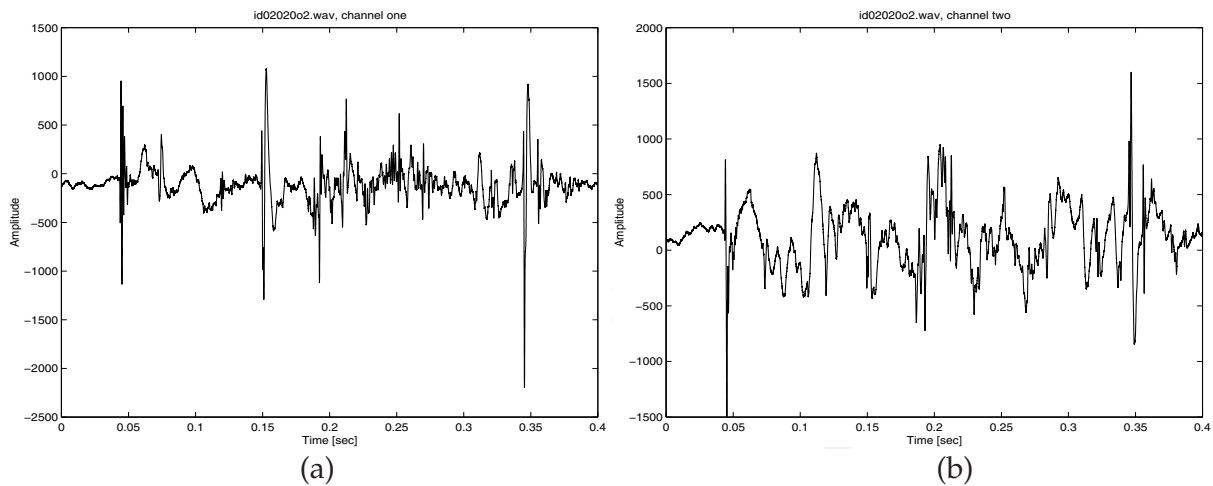


Fig. 5. Typical TMJ signals (crepitation).

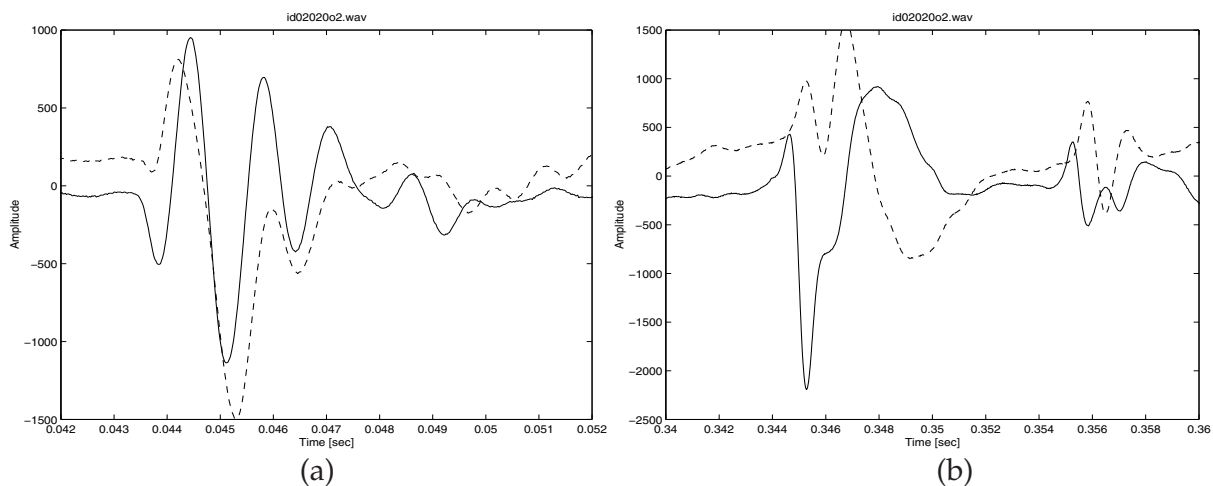


Fig. 6. The zoomed version of the typical TMJ signals (crepitation).

click interference, it estimates the first source for click TMJ with a π phase shift, while the DUET method failed to estimate both source signals as shown in Fig. 4(d).

On the other hand, the proposed source separation method outperforms the existing ones on real TMJ mixtures as well. With the extracted crepitation labeled in circles, one could observe that both the FastICA and DUET approaches estimate sources with overlapping crepitations (i.e. the crepitations occur at the same time in both sources). This indicates the ineffectiveness of the separation scheme which does not happen in the estimated sources by the proposed method.

In order to quantitatively evaluate the separation performance, we have used mutual information of two separated TMJ signals. The mutual information of two random variables is a quantity that measures the mutual dependence of the two variables. Mutual information of two random variables y_1 and y_2 can be expressed as

$$I(y_1; y_2) = H(y_1) + H(y_2) - H(y_1, y_2) \quad (9)$$

where $H(y_1)$ and $H(y_2)$ are marginal entropies, and $H(y_1, y_2)$ is the joint entropy of y_1 and y_2 . The value of mutual information (MI) for the pair of used mixture recording signals is

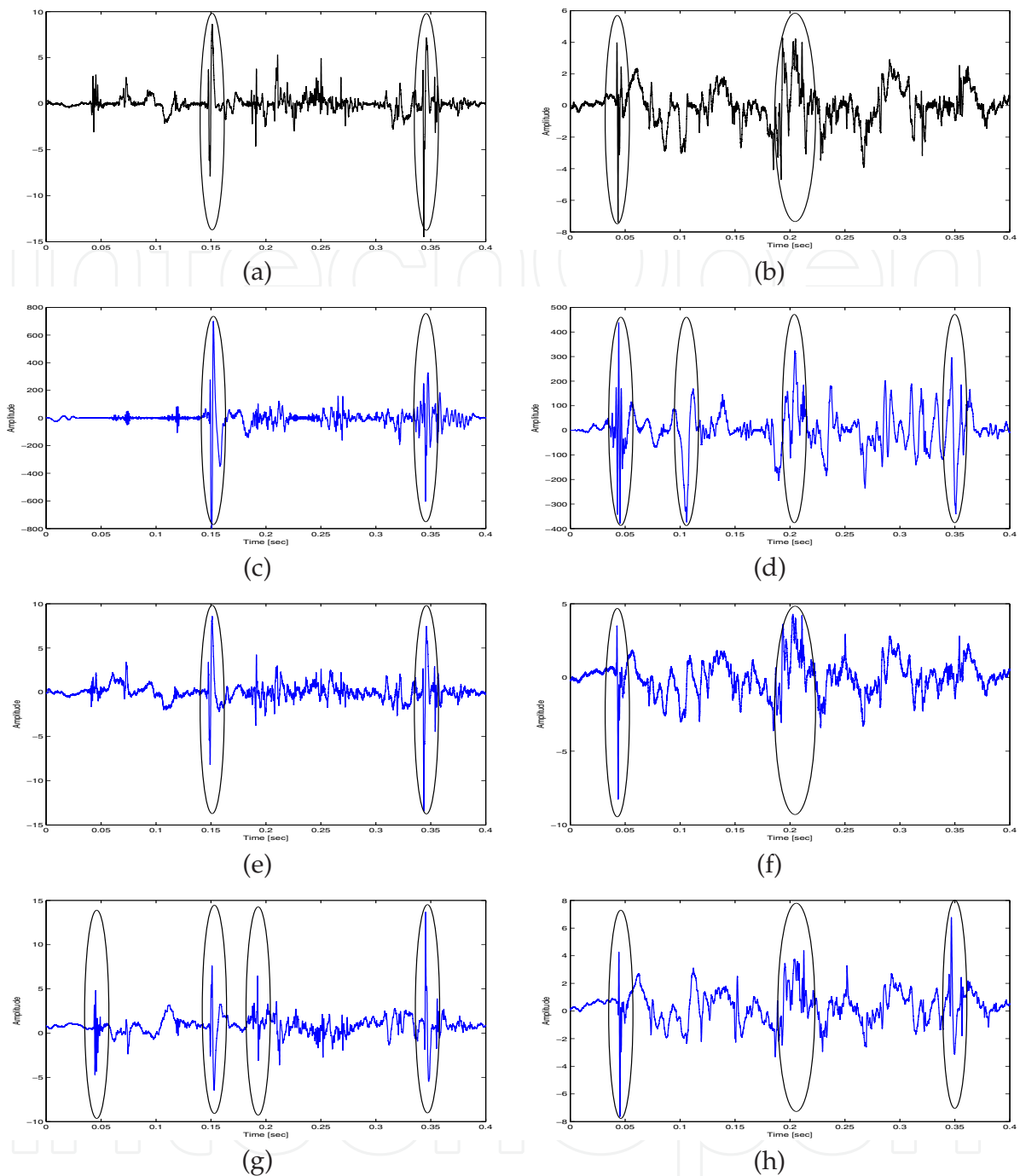


Fig. 7. The results of (a)(b) the proposed ICA based source extraction method; (c-d) DUET method in (Widmalm et al., 2002); (e-f) Infomax approach in (Guo et al., 1999); (g-h) FastICA approach in Hyvärinen et al (2000) on real TMJ recordings in Fig. 5.

0.5853 for the simulated TMJ signals and the MI value for the real TMJ recordings are 0.2770, and the respective average mutual information for the pair of source signals estimated by various methods are summarized in Table 1. It can be seen that, as compared to the existing approaches, this value for the source signals estimated by the proposed method is much lower than the value of mutual information of the mixture signals. Also, for the real TMJ recordings, the lower values of mutual information between the pair of estimates as obtained

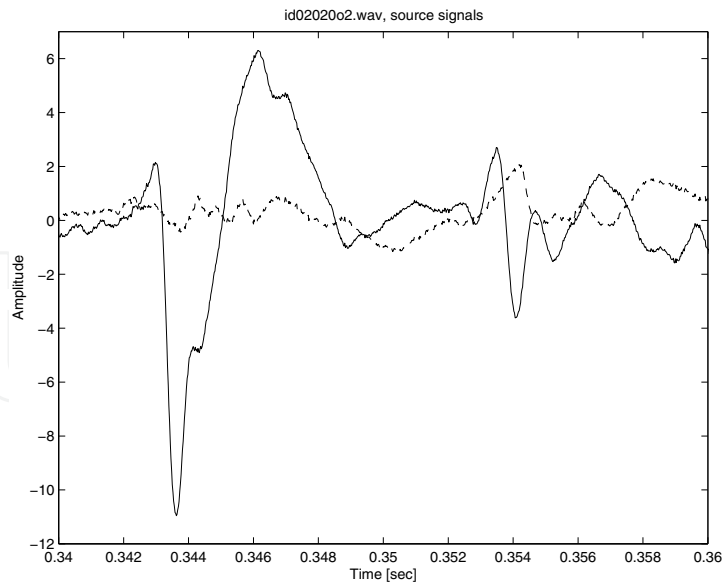


Fig. 8. The results of the proposed ICA based source extraction method (near 0.35s).

Method	Proposed ICA	DUET	Infomax	FastICA
Simulated				
TMJ Mixture	0.1275	0.4771	0.1296	0.4949
Real TMJ				
Recording	0.0812	0.1928	0.0875	0.2670

Table 1. The mutual information of the recovered/separated source signals by the proposed ICA based BSS and other existing methods in both simulated and real experiments

by the proposed method show that this ICA based source separation scheme achieves a better degree of statistical independence between their respective estimates than the Infomax and DUET estimates. Similar low values of mutual information has been observed between the pair of Infomax and the proposed ICA based estimates, which shows that both methods are able to achieve high degree of statistical independence between their respective estimates. Nevertheless, as compared to the Infomax estimates, the proposed method estimates the click source more accurately as depicted in Fig. 4. The averaged values of Pearson correlation between the simulated source and the estimated source obtained by the proposed ICA method, the DUET method, the Infomax method, and the FastICA method are 0.7968, 0.4524, 0.6686, 0.3355, respectively. The highest value by the proposed method indicates the high resemblance between the estimated and the actual sources.

To assess the robustness of the present scheme with respect to the noise effect, the performance of the proposed ICA based BSS method is also evaluated in the presence of additive noise. Pink noise and white Gaussian noise at various signal to noise ratio (SNR) have been added to the simulated TMJ mixtures.

The separation quality based on the estimated unmixing matrix $\hat{\mathbf{W}}$ obtained from simulated TMJ mixture and the actual mixing matrix \mathbf{H} for the noisy simulated TMJ mixtures has been computed as follow (Choi et al, 2000):

$$PI = \frac{1}{2} \left[\sum_{i=1}^{i=2} \left(\frac{\sum_{j=1}^{j=2} |G_{ij}|^2}{\max_{\kappa} |G_{i\kappa}|^2} - 1 \right) + \sum_{j=1}^{j=2} \left(\frac{\sum_{i=1}^{i=2} |G_{ij}|^2}{\max_{\kappa} |G_{\kappa j}|^2} - 1 \right) \right] \quad (10)$$

with $\kappa \in \{1,2\}$ and

$$\mathbf{G} = \hat{\mathbf{W}}\mathbf{H} = \begin{pmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{pmatrix}, \quad \hat{\mathbf{W}} = \begin{pmatrix} W^{11} & W^{12} \\ W^{21} & W^{22} \end{pmatrix} \quad (11)$$

Since the effect of additional noise has been estimated and ideally excluded from the estimated unmixing matrix $\hat{\mathbf{W}}$, the resulting index value PI should therefore give ideally consistent value of 0 (i.e. equivalent to negative large value in dB) with changing SNR.

The plot of performance index as defined in Eq. (10) vs SNR of the simulated noisy TMJ click signals with additive white Gaussian noise is illustrated in Fig. 9. We could observe that the PI remains at relatively low value as the level of the noise increases for the proposed method. In compare to other methods, the proposed method produces a relatively smaller values of PI . This result shows the robustness of the proposed scheme in the presence of noise.

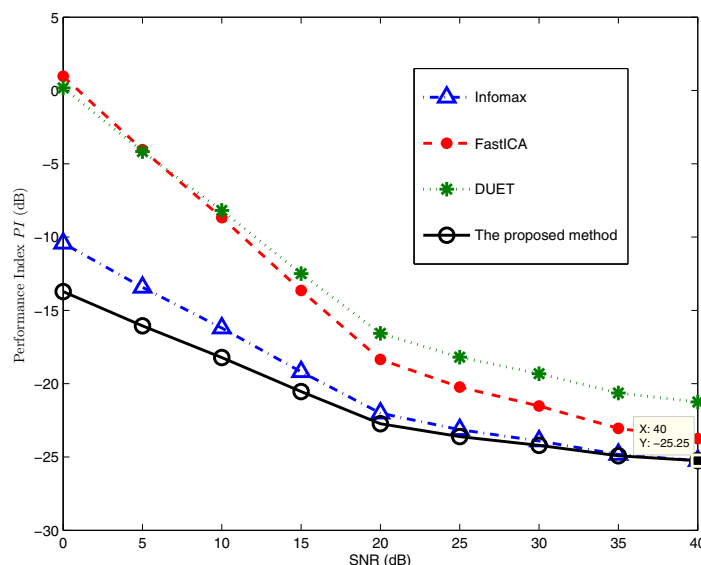


Fig. 9. Comparison of the noise resistance performance index PI by the proposed ICA based BSS method and other existing methods on simulated TMJ mixtures in the presence of white Gaussian noise.

The source separation performance is also evaluated by measuring the SNR gain of the extracted signals with respect to the original simulated source signals at various noise levels (Li et al, 2009). This SNR gain $\Delta SNR = SNR_{est} - SNR_{mix}$ of the estimated source signal is measured with

$$SNR_{est} = 10 \log_{10} \frac{\sum_t s^2(t)}{\sum_t (s(t) - \hat{s}(t))^2} \quad (12)$$

and

$$SNR_{mix} = 10 \log_{10} \frac{\sum_t s^2(t)}{\sum_t (s(t) - x(t))^2} \quad (13)$$

where $s(t)$ is the clean source signal prior to mixing, $\hat{s}(t)$ is the estimated source signal, and $x(t)$ is the mixture signal. The resulting gain is summarized in Fig. 10. Since the evaluation

is performed on the two-source condition, the average value of ΔSNR for two sources is adopted. As compared to other methods, the consistent higher SNR_{est} with decreasing SNR produced by the proposed method verifies the noise resistance of the proposed source extraction scheme from another aspect. Furthermore, the proposed method is more resistant to white Gaussian noise than it to pink noise by providing higher SNR gain value at low SNR.

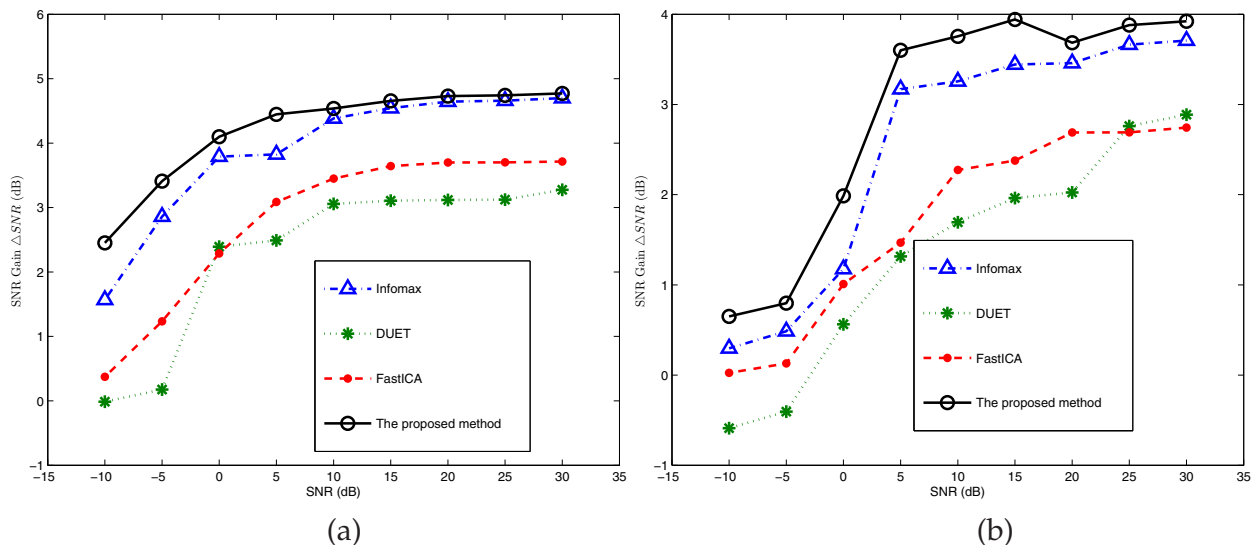


Fig. 10. The results of ICA based BSS method on simulated TMJ mixtures in the presence of (a) white Gaussian noise; and (b) pink noise.

9. Summary and discussion

In this article, it is shown that how ICA could play a vital role in order to develop a cheap, efficient and reliable diagnostic tool for the detection of temporomandibular joint disorders (TMD). The sounds from the temporomandibular joint (TMJ) are recorded using a pair of microphones inserted in the auditory canals. However, the TMJ sounds originating from one side of head can also be picked up by microphone at the other side. The presented ICA based method ensures that the signals used for the subsequent analysis are the actual source signals, and not contaminated by the sounds propagated from the contra side. The challenge of allocating the TMJ sound sources with respect to each side of the head has therefore been solved which provides an efficient non-invasive and non-intrusive procedure for TMD diagnosis.

The detailed technical issues together with elaborative results, quantitative evaluation as well as subsequent analysis have been presented in this chapter. In compared to the Infomax approach, the proposed ICA based method with adaptive parameters gives a better source separation performance and a higher noise resistance. Unlike any existing papers, the assumption that the two TMJ sound sources are non-overlapped in time-frequency (TF) domain has been removed here, and a more generalized mixing is considered by including the challenging source separation problem of two abnormal TMJ sounds which might be overlapped in TF domain. The proposed signal processing technique then allows for an enhanced clinical utility and an automated approach to the diagnosis of TMD.

10. Future directions

Since the anechoic head model is assumed in this paper, no reverberation of the sound sources is considered. A more generalized transmission models for the TMJ sounds would thus be discussed and compared together with the effects of the model parameters on the TMJ analysis in our future work. Although the general trend of blind source separation research makes use of linear models for source separation, it could also be possible to consider non-linear models for some complex systems (Ming et al, 2008) with additional constraints and assumptions. This topic therefore remains as a developing research area with a lot of potential for real-life.

Another interesting aspect of the problem could be the use of noise extracted from TMJ for the analysis of different types of non-stationarity to identify temporomandibular disorder (Ghodsi et al, 2009). Furthermore, it can be considered to extent ICA methods for 2D images in order to develop imaging methods in the diagnosis of temporomandibular joint disorders (Tvrđy, 2007). Besides, it could also be possible to further improve the TMD analysis performance assisted by a postprocessing scheme (Parikh, 2011). We would thus combine/fuse sound with the visual data such as those related to facial movement which are comfortable and safe to acquire, in order to further help the audio analysis to characterize TMD.

11. References

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