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BLIND SOURCE SEPARATION ON BIOMEDICAL FIELD BY USING NONNEGATIVE MATRIX FACTORIZATION

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ABSTRACT

The study of separating heart from lung sound has been investigated and researched for years. However, a novel approach based on nonnegative matrix factorization (NMF) as a skill of blind source separation (BSS) that utilized in biomedical field is fresh presented. Lung sound gives beneficial information regarding lung status through respiratory analysis. However, interrupt of heart sound is the obstacle from taking precise and exact information during respiratory analysis. Thus, separation heart sound from lung sound is a way to overcome this issue in order to determine the accuracy of respiratory analysis. This paper proposes factorizations approach that concern on the 2 dimensional which is combination of frequency domain and time domain or well known as NMF2D. The proposed method is developed under the divergence of Least Square Error and Kullback-Leibler and it demonstrates from a single channel source. In this paper, we will forms a multivariate data and it will proceed for dimension reduction by log frequency domain. Experimental tests and comparisons will be made via different divergence to verify and evaluate efficiency of the proposed method in term performance measurement.

Keywords: blind source separation, nonnegative matrix factorization, KL divergence, LSE divergence.

INTRODUCTION

Blind source separation (BSS) [1-2] depends on the assumptions of sources that are non-redundant or based on statistical independence, orthogonality and decorrelation. BSS significantly separate unknown sources without using training knowledge or additional data. It has been applied in different sort of field such as biomedical signal processing, remote sensing, exploration seismology, neural networks and etc. Approaches are considered as machine learning algorithm which is high speed, high robustness and high reliability that imposed to solve BSS problem such as nonnegative matrix factorization (NMF) [3-6], independent component analysis (ICA) [7-8], computational auditory scene analysis (CASA) [9-10] and etc. NMF is a useful decomposition for multivariate data. It is an unsupervised data (matrix) decomposition technique utilizing the sparse representation of data structures. The NMF algorithm based on multiplicative update (MU) rules is widely used in the fields of image and acoustic signal processing. Multiplicative update rules can minimize different divergence metrics and integrate easily with the basic NMF [11]. The advantage provided by NMF is it only requires single channel as input signal instead of multichannel which is usually required by other BSS methods [12].

BSS via NMF have been a popular topic of intense work in the biomedical signal processing and neural networks field. For the biomedical signal processing field, BSS technique has been used to separate heart sound and lung sound. As we know, human body is a complicated and sophisticated living organism which made up by millions and millions of tissues and cells. Besides the brain and heart, lung can be considered as the most complicate organ among the other organs in human body. Therefore, lung play important role in heartbeat system and respiratory system in such the way of offering enough oxygen in the entire of our life. Several types of information are used to analyze lung condition which is non-invasive diagnoses through lung sound recording [13]. A clearer lung sound recording will present a better performance of diagnose as well increase the accuracy of diagnose. However, it is difficult to achieve a 100% clearance of lung sound due to the interference of heart sound in term of time domain and spectral content during recording [14]. The overlapping of heart sound to lung sound will cause the heart sounds are clearly audible in lung sounds recorded on the anterior chest and maybe heard to a lesser extent in lung sounds recorded over posterior lung lobes. Hence, interference of heart sound to lung sound in a manner that reduces the potential of respiratory sound analysis in term of diagnoses the respiratory system disease which defers the time of medical-seeking advice.

DEFINITION OF LUNG SOUND AND HEART SOUND

The vertical and turbulent air flow within lung airway creates lung sound. Lung sounds result from the vibrations within the lung and its airways that are transmitted to the chest wall which vibration amplitude may be less than 10 µm [15]. It is also the effects of thoracic tissues and sound sensor characteristics on sound transmitted from the lungs to a data acquisition system. Power spectral density (PSD) presents a broadband with power decreasing as frequency increases. The flow of lung airways increasing as the sound intensity increases [16-17]. It is important that to distinguish the inspiratory sound and expiratory sound in term of time domain and spectral since the inspiratory sound will shows higher intensity compared to expiratory sound [18]. Therefore, the auscultation of helping in monitoring and diagnosis of pulmonary diseases will be improved in term of performance of signal when the interference of heart sound can be eliminated.

Heart produces blood and pumps out to the whole human body with the movement of in and out of heart which so called blood circulation. The heart first pumped the blood to the rest of the body will produce the first heart sound which is containing the sound of rise and release the pressure within left ventricle. The second heart sound will be caused by the blood when leaving ventricles and connecting to aorta and pulmonary arteries [19-20]. Considerable variability exists for heart sound PSD from a single patient and between normal patients, the use of adaptive filtering for heart-sound reduction may account for such variability since its parameters change with signal characteristics, as discussed in the two following sections.

PROPOSED METHOD

Nonnegative matrix factorization

The evolution of NMF is started from Lee and Seung. Basically, the NMF decomposes or factorize the complex matrix into 2 or more simple matrices or known as a useful constraint for matrix factorization that can learn a parts representation of the data [21].

In the forepart of evolution of NMF, given a nonnegative matrix V with the nonnegative matrix factors W and H in such way, $V \approx WH$. The vector is located in columns of a $n \times m$ matrix V where n is a set of multivariate n-dimensional data vectors and m is number of examples in data set. It is then factorized into $n \times r$ which is matrix W and $m \times r$ which is matrix H as shown in equation 2.

$$V \approx WH \quad (1)$$

$$n \times m = (n \times r) \cdot (m \times r) \quad (2)$$

The V is original non-negative data, W is matrix of basis vectors or dictionary elements and H is matrix of activations, weights, or gains. In other words, the Wcan be thought of as the 'building blocks' of the data and the H describes how strongly each 'building block' is present in the measurement vector V.The first thing is to find out the cost function. It is using a measurement of square of the Euclidean distance between two non-negative matrices V and Λ.

$$||V - \Lambda||^2 = \sum_{ij}\left(V_{ij} - \Lambda_{ij}\right)^2 \quad (3)$$

Another useful measure is:

$$D(V||\Lambda) = \sum_{ij}\left(V_{ij}\log\left(\frac{V_{ij}}{\Lambda_{ij}}\right) - V_{ij} + \Lambda_{ij}\right) \quad (4)$$

There are several multiplicative update rules which can be applied in above cost function corresponds to maximizing the likelihood of a gaussian noise model. The multiplicative update rule is including Least Square Error (LSE) divergence and Kullback-Leibler (KL) divergence [22]. LSE divergence and KL divergence extend into non-negative factor 2-D deconvolution (NMF2D) model:

$$V \approx \Lambda = \sum_{\tau}\sum_{\emptyset} \overset{\downarrow \emptyset}{W^{T}} \overset{\rightarrow \tau}{H^{\emptyset}} \quad (5)$$

Least square error divergence

Consider the least square cost function in NMF2D which corresponds to maximizing the likelihood of a gaussian noise model:

$$C_{LS} = \left||V - \Lambda|\right|_f^2 \quad (6)$$

$$= \sum_i\sum_j\left(V_{ij} - \Lambda_{ij}\right)^2 \quad (7)$$

Next, C_{LS} is differentiated by W^T as below:

$$\frac{\partial C_{LS}}{\partial W_{k,d}^{T}} = \frac{\partial}{\partial W_{k,d}^{T}}\sum_i\sum_j\left(V_{ij} - \Lambda_{ij}\right)^2 \quad (8)$$

$$= -2\sum_i\sum_j(V_{ij} - \Lambda_{ij})\frac{\partial \Lambda_{i,j}}{\partial W_{k,d}^{T}} \quad (9)$$

$$= -2\sum_{\emptyset}\sum_j\left(V_{\emptyset+k,j} - \Lambda_{\emptyset+k,j}\right)H_{d,j-\tau}^{\emptyset} \quad (10)$$

LSE divergence shows recursive updates converge to a local minimum as following formula:

$$H \leftarrow H\left(\frac{W^{T}V}{W^{T}WH}\right) \quad (11)$$

$$W \leftarrow W\left(\frac{H^{T}V}{H^{T}HW}\right) \quad (12)$$

Kullback-Leibler divergence

Consider the Kullback-Leibler (KL) divergence which corresponds to assuming multinomial noise model:

$$C_{KL} = \sum_i\sum_j V_{i,j}\log\frac{V_{i,j}}{\Lambda i,j} - V_{i,j} + \Lambda_{i,j} \quad (13)$$

Next, C_{KL} is differentiated by W^T as below:

$$\frac{\partial C_{KL}}{\partial W_{k,d}^{T}} = \frac{\partial}{\partial W_{k,d}^{T}}\sum_i\sum_j V_{i,j}\log\frac{V_{i,j}}{\Lambda i,j} - V_{i,j} + \Lambda_{i,j} \quad (14)$$

$$= \sum_i\sum_j\left(1 - \frac{V_{i,j}}{\Lambda i,j}\right)\frac{\partial \Lambda_{i,j}}{\partial W_{k,d}^{T}} \quad (15)$$

$$= \sum_{\emptyset}\sum_j\left(1 - \frac{V_{K+\emptyset,j}}{\Lambda_{K+\emptyset,j}}\right)H_{d,j-\tau}^{\emptyset} \quad (16)$$

KL divergence shows recursive updates converge to a local minimum as following formula:

$$W \leftarrow W\left(\frac{VH^{T}}{WHH}\right) \quad (17)$$

$$H \leftarrow H\left(\frac{W^{T}V}{WWH}\right) \quad (18)$$

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The transposed equation (1) interchanges the order of W^T and H^ϕ in the model for both divergences. In matrix notation the updates can be written as (Schmidt and Mørup, 2006).

$$W^T \leftarrow W^T \cdot \frac{\sum_\phi \overset{\uparrow\phi\rightarrow\tau^T}{V\, H^\phi}}{\sum_\phi \overset{\uparrow\phi\rightarrow\tau^T}{\Lambda\, H^\phi}} \tag{19}$$

$$H^\phi \leftarrow H^\phi \cdot \frac{\sum_\tau \overset{\downarrow\phi}{W^T} \overset{T\leftarrow\tau}{V}}{\sum_\tau \overset{\downarrow\phi}{W^T} \overset{T\leftarrow\tau}{\Lambda}} \tag{20}$$

Initialization on W and H
repeat divergence
for updating on KL divergence
$W \leftarrow W\left(\frac{VH^T}{WHH}\right)$
$H \leftarrow H\left(\frac{W^TV}{WWH}\right)$
Cost function for KL divergence
$C_{KL} = \sum_i \sum_j V_{i,j} \log \frac{V_{i,j}}{\Lambda i,j} - V_{i,j} + \Lambda_{i,j}$
Reconstruct V=WH
if not meet the stopping criterion
return repeat divergence
end if
end for
until reconstruct Λ

Figure-1. Summary of multiplicative updating rule by using KL divergence cost function for NMF [23].

Initialization on W and H
repeat divergence
for updating on LSE divergence
$\mathrm{H} \leftarrow \mathrm{H}\left(\frac{\mathrm{W^TV}}{\mathrm{W^TWH}}\right)$
$\mathrm{W} \leftarrow \mathrm{W}\left(\frac{\mathrm{H^TV}}{\mathrm{H^THW}}\right)$
Cost function for KL divergence
$\mathrm{C_{LS}} = \sum_\mathrm{i} \sum_\mathrm{j} \left(\mathrm{V_{ij}} - \Lambda_\mathrm{ij}\right)^2$
Reconstruct V=WH
if not meet the stopping criterion
return repeat divergence
end if
end for
until reconstruct Λ

Figure-2. Summary of multiplicative updating rule by using LSE divergence cost function for NMF [23].

PERFORMANCE MEASUREMENT OF BSS

The performance of BSS relies on application such as sometimes; the objective is to extract the source signals that are listened to, straight after separation or after some post-processing audio treatment or sometimes, it is to retrieve source features and/or mixing parameters to describe complex audio scenes in a way related to human hearing. Since that the mixing and demixing system do not need to be known, thus the performance measurement of BSS is important to differentiate the performance of different sound signals. Basically, the elements that used to compare will be original source and estimated source in term of Source to Distortion ratio (SDR), Source to Interference ratio (SIR) and Source to Artifact ratio (SAR) [24]. Original source, s_j denoted to the signal source is extracted from musical instrument or human voice before mixed up together. Estimated source, $\overline{s_j}$ denoted to the signal source that has been separated through algorithm mentioned above into 2 or more sources.

From estimated source decomposition to global performance measures

For Source to Distortion ratio,

$$\mathrm{SDR} = 10\log\left(\frac{\|s_{\mathrm{target}}\|^2}{\|\varepsilon_{\mathrm{interf}} + \varepsilon_{\mathrm{noise}} + \varepsilon_{\mathrm{artif}}\|^2}\right) \tag{21}$$

For Source to Interference ratio,

$$\mathrm{SIR} = 10\log\left(\frac{\|s_{\mathrm{target}}\|^2}{\|\varepsilon_{\mathrm{interf}}\|^2}\right) \tag{22}$$

For Source to Noise ratio,

$$\mathrm{SNR} = 10\log\left(\frac{\|s_{\mathrm{target}} + \varepsilon_{\mathrm{interf}}\|^2}{\|\varepsilon_{\mathrm{noise}}\|^2}\right) \tag{23}$$

For Source to Artifact ratio,

$$\mathrm{SAR} = 10\log\left(\frac{\|s_{\mathrm{target}} + \varepsilon_{\mathrm{interf}} + \varepsilon_{\mathrm{noise}}\|^2}{\|\varepsilon_{\mathrm{artif}}\|^2}\right) \tag{24}$$

The SDR, SIR, SNR and SAR are modified based on the idea of SNR. In our case, $\varepsilon_{\mathrm{interf}} \approx 0$, therefore, $\mathrm{SIR} \approx +\infty$ but SNR defined as $\mathrm{SNR} = 10\log\left(\frac{\|s_{\mathrm{target}}\|^2}{\|\varepsilon_{\mathrm{noise}}\|^2}\right)$ would give $\mathrm{SNR} \approx 0$ [23]. Hence, SNR will be neglected in our study.

EXPERIMENTAL RESULTS

In this paper, we work the proposed NMF2D based method which directly applied into biomedical field in such the way of separation on heart sound and lung sound. The experiment has been divided into 2 cases which is testing on KL divergence firstly and testing on LSE divergence secondly. This experiment is conducted through different simulations that used to make the comparison of efficiency between the original audio sources and estimated audio sources.

Experiment setup

All simulations and analyses are run via PC with Intel Core 2 Duo CPU 6750 at 2.66 GHz and 4GB RAM as well as laptop with Intel Core i5 CPU 5200 at 2.2GHz and 4GB RAM. Software that used to run this experiment is MATLAB 2010 which is using as programming platform. The mixed signal is sampled at 44.1 kHz sample rates. All cases are mixed with equal average power over the duration of signals which is normalizing the time domain in same decibel for all sources in order to get better performance during separation process. The time-frequency (TF) domain is computed by using STFT via

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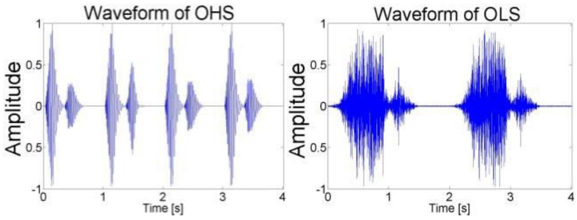
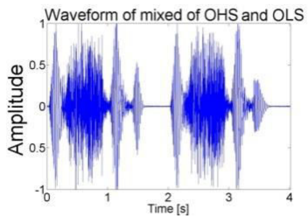
2048 point Hanning window FFT and the frequency domain it then logarithmically scaled. The convolutive components in time and frequency are selected to be $\tau = \{0,\ldots,3\}$ and $\phi = \{0,\ldots,31\}$ for both cases. In additions, the evaluation performance in terms of signal-to-distortion ratio (SDR), signal-to-interference ratio (SIR) and signal-to-interference ratio (SAR) is carrying on.

Performance of results

Firstly, by using the proposed approach, NMF2D with KL divergence, we had conducted several experiments in order to investigate the result after run the comparison of performance of different criteria. Secondly, we repeated the experiments on separation part by using same approach but different divergence which is LSE divergence.

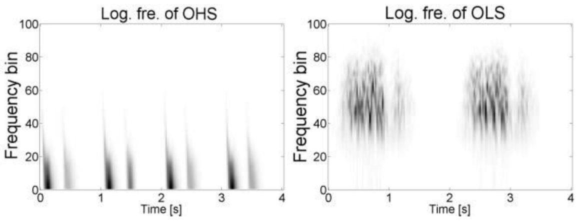


(a) (b)

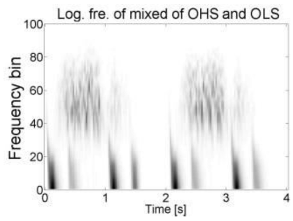


(c)

Figure-3. Time domain representation of (a) original heart sound (OHS), (b) original lung sound (OLS), (c) mixed of OHS and OLS.



(a) (b)



(b)

Figure-4. TF representation of (a) log. frequency of OHS, (b) log. frequency of OLS, (a) log. frequency of mixed of OHS and OLS

From the Figure-3 and Figure-4, we noted that the mixture shown that portion of waveform of lung sound is significantly larger than heart sound when heart and lung sound mixed together. This is because time interval for each period of heartbeat is significantly short compare to period of respiration. Thus, it features the overlapping of heart and lung sound which prepare a challenge for BSS. A spectrogram is a visual representation of the frequency content of a signal which is showing how the quantity of energy in different frequency regions varies as a function of time. The shade of colour is changing upon the intensity of the sound or audio. The aterrimus or known as deep black colour delegates the highest intensity of sound, it then fades out to become charcoal grey and turns into light grey of the aterrimus. This means that the intensity of sound is reducing over certain time period, but it increases again the over another time period. The deeper the colour representation, the higher the intensity of sound, the more significant listener might be heard.

Separation using KL divergence

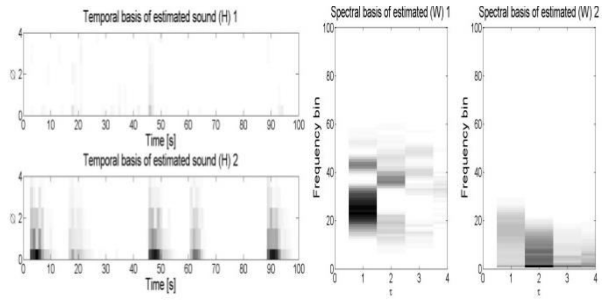
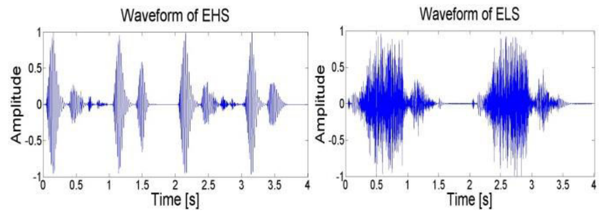
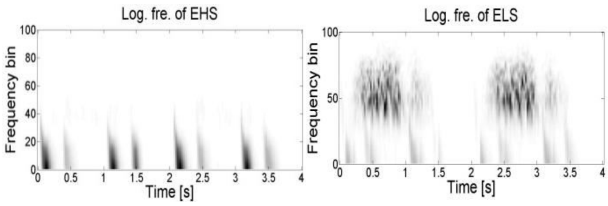


Figure-5. Estimated W and H using KL divergence after separation.



(a) (b)



(c) (d)

Figure-6. Time domain representation of (a) estimated heart sound (EHS), (b) estimated lung sound (ELS) and TF representation of (a) log. frequency of EHS, (b) log. frequency of ELS.

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Separation using LSE divergence

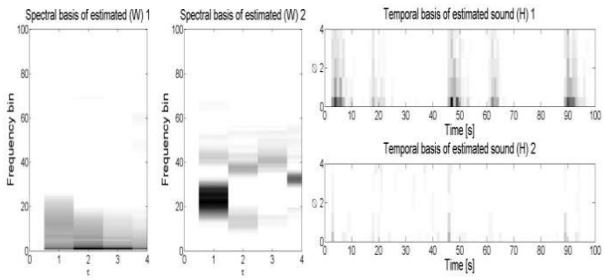

Figure-7. Estimated W and H using LSE divergence after separation.

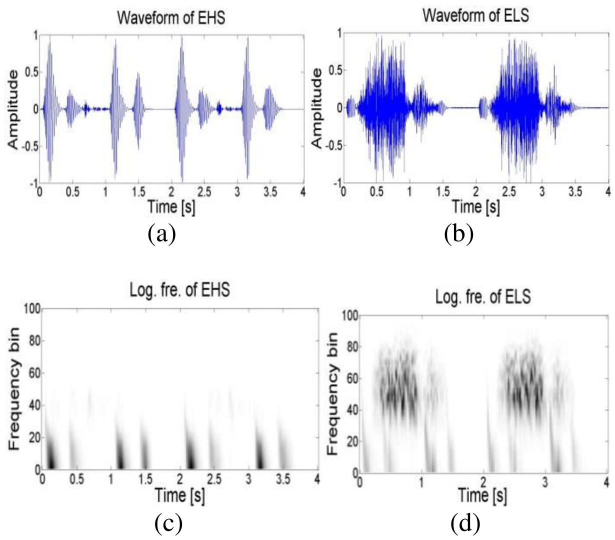

Figure-8. Time domain representation of (a) EHS, (b) ELS and TF representation of (a) log. Frequency of EHS, (b) log. frequency of ELS.

Figure-5 and Figure-6 show that the estimated heart and lung by using KL divergence. Conversely, Figure-7 and Figure-8 show the result through LSE divergence applied. Figure-5 and Figure-7 show the estimated W and H element after separation. W indicates spectral basis and H indicates temporal codes. By the same token, H denotes moves each element in the matrix by τ column to the right. The multiplication in between W and H will become the separated element. For instance, in Figure-5, by multiplying upper panel of H with left panel of W, it will reconstruct into source element and so forth.

By comparing the Figure-3 (a), (b) to Figure-6 (a), (b) and Figure-8 (a), (b), the waveform of estimated individual heart and lung sound is kinda disparity to waveform of original individual heart and lung sound. This is because in mixture of heart and lung sound, there is small portion of original heart sound intersperses in certain portion of lung sound during separation and vice-versa. Redundant of heart sound signal in lung sound signal will makes separation cannot be finished perfectly which conventional or other NMF method cannot be done as well. Besides, according to Figure-6 (d) and Figure-8 (d), it shown there is a redundant signal in bottom part of its spectrogram which means the sparse of heart sound signal is left in it. However, overall of separation is done satisfactory because the colour of redundant signal is certainly light shade. This means the intensity and energy of it is not high enough in order to overcome the mainstream sound.

Table-1 and Table-2 shows the comparison on performance measurement of heart and lung sound on different divergence. Basically, there are 2 types of unwanted signal in the reconstruction of signal. Firstly, noise due to mis-separation which so called *interferences*. The interference defines as the residual of unwanted signal during reconstruction of signal after separation. Secondly, noise due to the reconstruction algorithm itself which is known as *artifact.* The artifact is some glitches due to the STFT phase estimation process. From the equation 30, 31 and 33, it shows the relationship of SDR, SIR and SAR is reciprocal to the $\varepsilon_{\text{interf}} + \varepsilon_{\text{noise}} + \varepsilon_{\text{artif}}$, $\varepsilon_{\text{interf}}$ and $\varepsilon_{\text{artif}}$respectively. This means that the higher the integer of SDR, SIR and SAR, the lower the energy of interference, noise and artifact. The reading of SDR, SIR and SAR is evenly obtained through the best 5 options from 10 times of each simulation recordings.

Table-1. The comparison on performance measurement of original and estimated heart and lung sound in normal and abnormal condition by using KL divergence.

Mixture	Comparison	**SDR** (dB)	**SIR** (dB)	**SAR** (dB)
Normal heart sound and normal lung sound	Original heart sound with estimated heart sound	20.2237	26.4032	21.5079
	Original lung sound with estimated lung sound	13.9835	14.8733	21.4476

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Table-2. The comparison on performance measurement of original and estimated heart and lung sound in normal and abnormal condition by using LSE divergence.

Mixture	Comparison	**SDR** (dB)	**SIR** (dB)	**SAR** (dB)
Normal heart sound and normal lung sound	Original heart sound with estimated heart sound	20.1240	25.8317	21.5950
	Original lung sound with estimated lung sound	13.4084	14.2014	21.6114

In Table-1, the average of SDR, SIR and SAR revealed that the lowest dB is SDR and the highest dB is SAR for both divergences. This indicates that the fewest of artifact error due STFT phase estimation process is occurred compared to SDR and SIR. Although SDR is the lowest compared to SIR and SAR, it still considered acceptable because the energy of interference and noise is low which produces sparse of unwanted signal. However, SDR that using KL divergence are slightly higher than measurement of LSE divergence. The difference in between 2 divergences of 2 estimations of SDR is 0.0997dB and 0.5751dB. In other words, SDR that using KL divergence are higher than LSE divergence about 0.49% and 4.11% respectively. Therefore, the KL divergence is slightly better than LSE divergence in term of SDR even though both considered satisfy.

CONCLUSIONS

This paper presents a novel technique which is NMF2D that applies in a new biomedical field on separating lung sound from lung sound. In the aspect of spectral basis and temporal basis, the proposed method, NMF2D yields obvious improvement in single channel BSS compared to the conventional NMF method. In addition, no matter separation on normal heart and normal lung sound or abnormal heart and abnormal lung sound, SDR, SIR and SAR all are not merely having positive integer but also decidedly having a large increment in term of dB compared to conventional NMF method. Besides, the method NMF with KL divergence is better than LSE divergence after several experiments are conducted in term of measurement performances. Although the result of performance measurement indicates satisfied thoroughly, it yet to be prefect and future research will attempt to address the points in order to achieve at a more accurate or nearly perfect solution.

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