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A STUDY OF BLIND SOURCE SEPARATION USING NONNEGATIVE MATRIX FACTORIZATION

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ABSTRACT

During the past decades, there are several methods or techniques have been proposed to improve the blind source separation (BSS) in signal processing field. One of the methods has been declared as useful technique which is nonnegative matrix factorization (NMF). This paper is presenting a theoretical study on NMF approach which coordinated with 4 divergences which are Least Square Error (LSE) divergence, Kullback-Leibler (KL) divergence, Itakura-saito (IS) divergence and Beta divergence. In which these 4 divergences are normally applied in nonnagetive matrix factorizarion 2 dimensions (NMF2D). Therefore, a novel techniques using machine learning algorithm which is fast, robust and reliable will be discussed in this paper based on most recent BSS technology. Besides that, a discussion and comparison on the different studies of BSS via NMF approach through various applications from different researchers or scholars.

Keywords: blind source separation, nonnegative matrix factorization, acoustic signal processing.

INTRODUCTION

Signal processing has been rapidly developing in recent years. Blind source separation becomes the popular topic in the neural network community (Hyvarinen, 1999), (Cichocki and Unbehauen, 1996), (Xiang, Kui Ng and Khanh Nguyen, 2010), signal processing community (Cardoso and HvamLaheld, 1996), circuits and systems society (Yin, Mei and Wang, 2007). This topic has been discussed extensively (Cichockiand Amari, 2003). As we know, without the assistance of information about the source signals or the mixing process, a set of source signals from a set of mixed signals can be separated. It is known as blind source separation or blind signal separation.

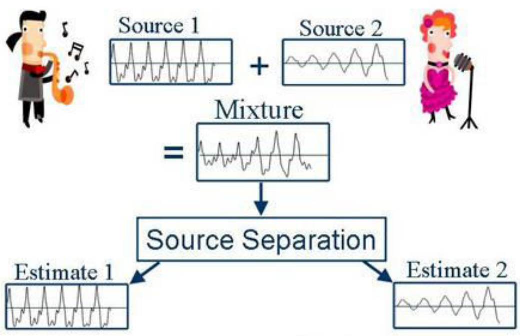

Figure-1. The basic idea of blind source separation.

Figure-1 shows the basic idea of blind source separation. It has been applied in different fields such as neural networks, advanced statistics, data mining, and biomedical signal/image processing. Blind source separation typically relies on the assumption that the sources are non-redundant, and the methods are based on statistical independence, orthogonality or decorrelation. It is mostly based on unsupervised learning and in principal; do not assume any prior information in the form of desired training data, signal distributions or parameters of mixing systems (Cichocki and Amari, 2003).

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 (Tjoa and Ray Liu, 2010).

The nonnegativity constraints using a wide class of loss functions, which leads to an extended class of multiplicative algorithms with regularization (Cichocki, 2006). NMF was first introduced by Paatero and Tapper as the concept of Positive Matrix Factorization, which concentrated on a specific application with Byzantine algorithms. It is continued introduced and popularized by Lee and Seung, it is an effective matrix factorization method for decomposing multivariate data under the constraints of nonnegative components. 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 (Leeand Seung, 1999). Most of NMF is sensitive to noise and outliers. The solution for this issue is using the algorithm that uses the projected gradient descent method to minimize the robust statistic energy function and yields two equations updated alternatively. The proposed of this NMF is known as robust convolutive nonnegative matrix factorization. It is dissimilar to other NMF which it can resistant to noise and outliers (Ye, Wenquan, Guojin and Yong, 2009).

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$$\begin{bmatrix} aA+bG & aB+bH & aC+bI & aD+bJ & aE+bK & aF+bL \\ cA+dG & cB+dH & cC+dI & cD+dJ & cE+dK & cF+dL \\ eA+fG & eB+fH & eC+fI & eD+fJ & eE+fK & eF+fL \\ gA+hG & gB+hH & gC+hI & gD+hJ & gE+hK & gF+hL \end{bmatrix} \approx \begin{bmatrix} a & b \\ c & d \\ e & f \\ g & h \end{bmatrix} x \begin{bmatrix} A & B & C & D & E & F \\ G & H & I & J & K & L \end{bmatrix}$$

Figure-2. Example of the matrix of V ≈ WH.

EVOLUTION OF NMF

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 (Lee and Seung, 1997).

In the forepart of evolution of NMF, given a nonnegative matrix V with the nonnegative matrix factors W and H in such way, V ≈ WHas shown as Figure-2. 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.

$$V \approx WH \tag{1}$$

$$n \times m = (n \times r) \cdot (m \times r) \tag{2}$$

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 A and B.

$$||A - B\,||^2 = \sum_{ij}\left(A_{ij} - B_{ij}\right)^2 \tag{3}$$

Another useful measure is:

$$D(A||B) = \sum_{ij}\left(A_{ij}\log\left(\frac{A_{ij}}{B_{ij}}\right) - A_{ij} + B_{ij}\right) \tag{4}$$

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 LSE divergence, KL divergence, IS divergence and Beta divergence (Lee and Seung, 2001). LSE divergence and KL divergence extend into non-negative factor 2-D deconvolution (NMF2D) model:

$$A \approx B = \sum_\tau \sum_\emptyset \overset{\downarrow \emptyset}{W^T}\; \overset{\to \tau}{H^\emptyset} \tag{5}$$

Least square error divergence

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

$$C_{LS} = \left||A - B|\right|_f^2 \tag{6}$$

$$= \sum_i \sum_j \left(A_{ij} - B_{ij}\right)^2 \tag{7}$$

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

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

$$= -2\sum_i \sum_j (A_{ij} - B_{ij}) \frac{\partial B_{i,j}}{\partial W_{k,d}^T} \tag{9}$$

$$= -2\sum_\emptyset \sum_j \left(A_{\emptyset+k,j} - B_{\emptyset+k,j}\right) H_{d,j-\tau}^\emptyset \tag{10}$$

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

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

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

Kullback-Leibler divergence

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

$$C_{KL} = \sum_i \sum_j A_{i,j} \log\frac{A_{i,j}}{Bi,j} - A_{i,j} + B_{i,j} \tag{13}$$

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

$$\frac{\partial C_{KL}}{\partial W_{k,d}^T} = \frac{\partial}{\partial W_{k,d}^T}\sum_i \sum_j A_{i,j} \log\frac{A_{i,j}}{Bi,j} - A_{i,j} + B_{i,j} \tag{14}$$

$$= \sum_i \sum_j \left(1 - \frac{A_{i,j}}{Bi,j}\right)\frac{\partial B_{i,j}}{\partial W_{k,d}^T} \tag{15}$$

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

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

$$W \leftarrow W\left(\frac{AH^T}{WHH}\right) \tag{17}$$

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

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

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$$W^T \leftarrow W^T \cdot \frac{\sum_{\emptyset} \overset{\uparrow\emptyset \rightarrow \tau^T}{A} H^{\emptyset}}{\sum_{\emptyset} \overset{\uparrow\emptyset \rightarrow \tau^T}{B} H^{\emptyset}} \quad (19)$$

$$H^{\emptyset} \leftarrow H^{\emptyset} \cdot \frac{\sum_{\tau} \overset{\downarrow\emptyset}{W^T} \overset{T \leftarrow \tau}{A}}{\sum_{\tau} \overset{\downarrow\emptyset}{W^T} \overset{T \leftarrow \tau}{B}} \quad (20)$$

Itakura-saito divergence

For the Itakura-saito divergence (Lefevre, Bach and Fevotte, 2011), it been defined as$d_{IS}(A,B) = \sum_i \left(\frac{A_i}{B_i} - \log\frac{A_i}{B_i} - 1\right)$. Itakura-saito divergence consists in finding W and H to minimize the below function:

$$L_H(W) = \frac{1}{N}\sum_{n=1}^{N} d_{IS}(v_n, Wh_n) \quad (21)$$

It then replaced by auxiliary function of the form of $L_H\big(W, \widetilde{W}\big)$ as shown as below:

$$L_H\big(W, \widetilde{W}\big) = \sum_{fk} A_{fk}\frac{1}{W_{fk}} + B_{fk}W_{fk} + c \quad (22)$$

Where,

$$A_{fk} = \sum_{n=1}^{N} H_{kn}V_{fn}\big(\widetilde{W}H\big)_{fn}^{-2}\widetilde{W}_{fk}^{2} \quad (23)$$

$$B_{fk} = \sum_{n=1}^{N} H_{kn}\big(\widetilde{W}H\big)_{fn}^{-1} \quad (24)$$

$$C = \sum_{f=1}^{F}\sum_{n=1}^{N} \log\frac{V_{fn}}{(\widetilde{W}H)_{fn}} - F \quad (25)$$

Beta divergence

Beta divergence or known as β-divergence (Févotteand Idier, 2011) is a family of cost functions parametrized by a single shape parameter β that takes the Euclidean distance, the Kullback-Leibler divergence and the Itakura-Saito divergence as special cases which is β = 2, 1, 0 respectively. It was introduced by Basu *et al*, Eguchi and Kano which defined as

$$d_\beta(A|B) = \begin{cases} \frac{1}{\beta(\beta-1)}\big(A^\beta + (\beta-1)B^\beta - \beta AB^{\beta-1}\big) \\ A(\log A - \log B) + (A - B) \\ \frac{A}{B} - \log\frac{A}{B} - 1 \end{cases} \quad (26)$$

$$\begin{aligned} &\beta \in \mathbb{R}\{0,1\} \\ &\quad \beta = 1 \\ &\quad \beta = 0 \end{aligned} \quad (27)$$

It is interpolated between the KL divergence (β = 1), the Euclidean distance (β = 2) and the IS divergence as a special limit case ($\beta = 0$) Auxiliary function is exhibited for β – divergence and it is defined as $\mathbb{R}_+^K \times \mathbb{R}_+^K \rightarrow \mathbb{R}_+$ mapping to$G(h|\overline{h})$. It is a majorizing function or upper bound of C(h) which is tight for h = $\overline{h}$ and it can be replaced by iterative optimization of $G(h|\overline{h})$.Considering the high demand, researchers have started searching the solution on enhancement of the NMF approach. In this paper, several techniques and algorithms that applied in NMF approach have been reviewed. Table-1 presents a summary of the different studies on BSS via NMF approach on various applications from different researchers or scholars. The studies are arranged chronologically, thus information on trends and development can be obtained. It is also the contribution of researchers or scholars on the improvement of NMF by supplanting with different algorithms or methods.

Table-1 explained that the different type of NMF used in BSS for various applications. Most of the application is based on the concept of audio or sound separation. It can be shown from the journal above that is number 2-3, 5-6, 8-10. The journal no.2 shows that separate polyphonic music which is same as journal no.3 that separate drum sound from the music. The journal no.9 and 10 are also showing the separation of speech from the music. The journal no.5 and 6 are showing the audio source separation. The journal no.8 is about the improvement of the performance and quality of the medical monitoring which is separating the heart sound and lung sound to differentiate the nuance. The different type of NMF has been applied in the above applications such as improved NMF, multilayer NMF, nonnegative matrix partial co-factorization (NMPCF), sparse NMF, and segmental NMF and so on. The improved NMF can separate the observed signals without reference source signal as well as features simple algorithm, fast speed, and real-time data processing. Compared to improved NMF, MNMF cannot separate effectively the independent source signals that are approximate in the amplitude.For NMPCF, it distinguishes the drum sound and the harmonic sound by using decomposition model as shown as following:

$$X = U_D V_D^T + U_H V_H^T \quad (28)$$

Comparison of the original signals with the residual of original and separated signals through formula below:

$$SNR = 10\log\frac{\sum s(n)^2}{\left(\sum s(n) - s'(n)\right)^2} \quad (29)$$

where, $s(n)$ is the original signal and $s'(n)$ is the separated signal. Nevertheless, the performance depended on the target song, NMPCF usually worked better than nonnegative matrix factorization with support vector machine (NMF+SVM). This is because the failure in the decomposition in NMF or in classification process leads to the low performance of the results. Thus, NMPCF showed better or almost comparable results to NMF+SVM. In addition, for the sparse NMF, its algorithm makes better speech quality compared to NMF algorithm which has poor speech quality but almost eliminates the noise. Besides that, the segmental NMF speech enhancement scheme was proposed for improving the conventional

NMF-based method in the way of frame-wise NMF based method. Compared to the conventional

Table-1. Summary of the different studies on BSS via NMF approach on various applications from different researchers or scholars.

No.	Year	Scholar(s)/Researcher(s)	Focus of study
1	2008	Gang Xu and Junyi Wu	A Removal of Power Line Interference in Signal Based on ImprovedNonnegative Matrix Factorization (Xu and Wu, 2008)
2	2010	Minje Kim, JihoYoo, Kyeongok Kangand Seungjin Choi4	Blind Rhythmic Source Separation: Nonnegativity And Repeatability (Yoo, Kim, Kang and Choi, 2010)
3	2010	JihoYoo, Minje Kim, Kyeongok Kang and Seungjin Choi	Nonnegative matrixpartial co-factorization for drum source separation (Yoo, Kim, Kang and Choi, 2010)
4	2011	Felix Weninger, Alexander Lehmannand Bj¨orn Schuller	Openblissart: Design And Evaluation Of A Research Toolkit ForBlind Source Separation In Audio Recognition Tasks (Weninger, Lehmann and Schuller, 2011)
5	2011	Emad M. Grais and Hakan Erdogan	Single Channel Speech Music Separation Using Nonnegative MatrixFactorization and Spectral Masks (Grais and Erdogan, 2011)
6	2012	Seokjin Lee, SangHa Parkand Koeng-Mo Sung	Beamspace-Domain Multichannel NonnegativeMatrix Factorization For Audio Source Separation (Lee and Ha Park, 2012)
7	2012	Luying Sui, Xiongwei Zhang, Jianjun Huang, Gaihua Zhao and Yan Yang	Speech Enhancement Based on Sparse Nonnegative MatrixFactorization with Priors (Sui, Zhang, Huang, Zhao, and Yang, 2012)
8	2013	ChingShun Lin and Erwin Hasting	Blind Source Separation of Heart and Lung SoundsBased On Nonnegative Matrix Factorization (Lin and Hasting, 2013)
9	2014	Miguel ArjonaRam´ırez	Nonnegative Factorization of Sequences of Speech and Music Spectra (ArjonaRam´ırez, 2014)
10	2014	Hao-Teng Fan, Jeih-weih Hung, Xugang Lu, Syu-Siang Wang and Yu Tsao	Speech Enhancement Using Segmental Nonnegative MatrixFactorization (Fan, Hung, lu, Wang and Tsao, 2014)
11	2014	Yun Li, Student, K. C. Ho, Fell and MihailPopescu	Efficient Source Separation Algorithms for Acoustic Fall Detection Using a Microsoft Kinect (Li, Hoand Popescu,2014)

NMF, the enhanced spectrograms derived by these sub-matrices characterized speech signals more explicit.

APPLIED INTHERAPEUTIC AND MEDICAL FIELD

Blind source separation is a fruitful method and advantageous to various aspects like therapeutic and medical field, musical tuning system, acoustic source separation and so on. In the aspect of therapeutic and medical, respiratory analysis and lung status can be inspected through lung sound. Lung sound is the breathing-related sound heard from the chest of healthy person. The effect the sound transmission amplitude and timing from airways to the chest surface will be changed due to the changes of lung structure that found in disease. It is also the most directly accessible information by simply using a stethoscope. A clean lung sound recording increases the accuracy of diagnosis. However, the interference of heart sound will create confusion when obtained the data of lung sound and it will lead to drop down the accuracy of diagnosis. Therefore, a novel approach based on NMF as one of BSS techniques is proposed in the event of mixing of lung and heart sound (Lin and Hasting, 2013). Furthermore, BSS can be applied in acoustic fall detection system (acoustic FADE). From the Figure-3, it shows that the Segment of mixture signal when receiving the fall detection in acoustic FADE.

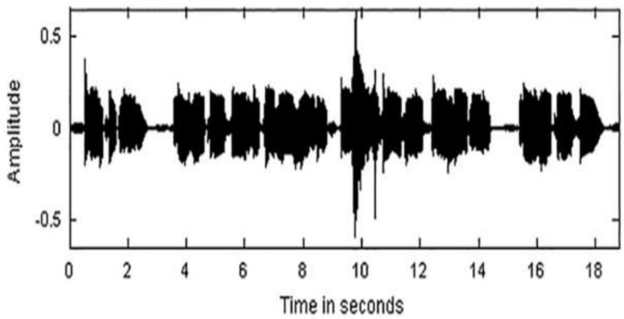

Figure-3. Segment of mixture signal which contains both a fall and a TV audio signal in the acoustic FADE (Li, Hoand Popescu, 2014).

Acoustic FADE is meaning of automatically signal a fall to the monitoring caregiver. The difficulties in acoustic FADE when detecting the fall signal in environments where interference comes from the fall direction, the number of interferences exceeds FADE's ability to handle or a fall is occluded. Thus, to address these issues, two blind source separation (BSS) methods for extracting the fall signal out of the interferences to improve the acoustic FADE. By using single channel blind source separation (SCBSS) and multichannel blind source separation (MCBSS) with NMF, based on the distinct patterns of the bases of falls, the identity of fall signal can be analyzed efficiently and then construct the interference free fall signal. The results show that in environments with high interference and background noise levels, the fall detection performance is significantly improved using the proposed BSS approaches.

APPLIED INACOUSTIC SOURCE SEPARATION

For the acoustic source separation, the conventional multichannel blind source separation algorithm was performing well in multichannel real-world recording data. However, the improvement of multichannel blind source separation still can be done by developing a multichannel blind source separation algorithm based on a beam space transform and the multichannel nonnegative matrix factorization (MC-NMF) method. The decomposition algorithm is applying to 2-channel and 4-channel unsupervised audio source separation by using a dataset from the international Signal Separation Evaluation Campaign 2010 (SiSEC 2010). The MC-NMF method with beam space transform notably enhances the SIR and ISR performance. As the channel number increases, the beam space transform becomes more meaningful, thus the performance of the proposed algorithm improves (Lee and Ha Park, 2012).

The performance of any speech recognition system is very sensitive to the supplementary music or sound to the speech signal. It is preferable to remove the music from the background of the speech to improve the recognition accuracy. The single channel blind source separation (SCBSS) which is based on NMF with spectral masks has been proposed. The additional technique on NMF which spectral masks can lead to improve the separation process even when calculating NMF with fewer iteration, which yields a faster separation process. NMF has been found in effectively solving the problem of single channel source separation (SCSS) because only one measurement of the mixed signal is available. The combination conventional NMF with sparse coding and statistical noise models which known as improved Sparse Nonnegative Matrix Factorization (ISNMF) also had been validated in the contribution of speech enhancement. Besides, a segmental NMF (SNMF) speech enhancement scheme is proposed to improve the conventional NMF method. Through the use of 2 algorithms which are in spectral domain based and temporal domain based, noisy speech signals can be modeled more precisely (Grais and Erdogan, 2011), (Sui, Zhang, Huang, Zhao and Yang, 2012), (Fan, Hung, lu, Wang and Tsao, 2014).

In addition, speech source separation can be done through the short-term Fourier transform (STFT) which is used with the Kullback-Leibler divergence (KLD) while its power spectral density is applied with the Itakura-Saito divergence (ISD). It is performed in the synthesis phase by factorization with compound bases using unsupervised NMF while the bases may be exemplar spectra randomly selected in an unsupervised manner (ArjonaRam´ırez, 2014).There is another issue that can be solved by NMF. Power line interference is a common interference source with low frequency and weak amplitude in Signal detection and transmission. To guarantee the reliability and accuracy of signal measure activities, the power line interference should be inhibited effectively. Thus, an improved approach of NMF which is multilayer NMF (MNMF) that can devote to bypass parameter estimate in power line and no independent reference signals. It has no strict constraints in observed signals and furnishes a solution of frequency drift. This approach features simple algorithm, fast speed, and real-time data processing (Xu and Wu, 2008).

The different approaches of NMF were compared via performance of speech separation which measure by signal to interference ratio (SIR) (Vincent, Gribonval and Févotte, 2006). The SIR resembles as signal to noise ratio (SNR) which means that SIR is the quotient between the level of target signal to level of background or undesired noise. The formula of SIR is

$$SIR = 10\log\frac{|s_{target}|^2}{|e_{interference}|^2} \quad (30)$$

The formula above represents the SIR is directly proportional to the square of target signal and inversely proportional to the square of interference signal. In other words, the increase of target signal will lead to the increment of SIR and vice versa with the circumstances of interference signal. From the statements and table above, the performance of speech separation by supervised and unsupervised NMF with Kullback-Leibler divergence and MNMF measured by SIR at various scopes. The tested scope in supervised an unsupervised NMF with Kullback-Leibler divergence is signal to music ratio (SMR) meanwhile in MNMF is layer of NMF. The table 2 shown that the regardless the method used, the higher the SMR or more layers, the higher the SIR. This is because SIR is directly proportional to target signal which means the signal transmission of target signal is stronger. In the midst of three methods, the MNMF is giving out highest SIR. Due to this factor, MNMF is proposed to bypass parameter estimate in power line in order to prohibit power line interference. On the other hand, the C++ framework and toolbox which named as open-source Blind Source Separation for Audio Recognition Tasks (open BliSSART) that has been used in a multiplicity of research on blind audio source separation and feature extraction successfully.

It provides the first open-source implementation of a widely applicable algorithmic framework based on NMF. Besides, it applies in Music Information Retrieval (MIR) and automatic speech recognition (ASR).Through openBliSSART, enhancement of robustness of ASR by separating the wanted speech from disturbance signals such as background noise or voice from other speakers as well as extracting mixture model and source model from

Table-2. The comparison on performance of speech between different methods of NMF.

Method	**Tested scope in SMR** (dB) **and layers**	**SIR** (dB)
Unsupervised NMF with Kullback-Leibler divergence	0 dB	1.2
	5 dB	6.4
	10 dB	11.3
	15 dB	16.6
Supervised NMF with Kullback-Leibler divergence	0 dB	2.1
	5 dB	7.0
	10 dB	11.9
	15 dB	17.1
MNMF	1 layer	14.72
	5 layers	87.89
	10 layers	131.26

monophonic signals (Weninger, Lehmann and Schuller, 2011). On the other hand, in order to enhance the performance of various musical information research (MIR) including automatic music transcription, musical similarity analysis, query by humming, and music classification, an extension of NMF which named as (nonnegative matrix partial co-factorization) NMPCF approach has been utilized for separating the monaural and binaural blind rhythmic source separation. The NMPCF was developed to improve the nonnegative matrix co-factorization and to allow partial-sharing of basis vectors with the other input matrices in order to separate drum sources (Yoo, Kim, Kang and Choi, 2010). It is used in source-specific characteristics for separating or extracting the source which focuses on extracting rhythmic sources from the mixture with the other harmonic source. It is better than conventional method in manner of applicability. The sparse or part-based NMF is used for automatic transcription of percussive or polyphonic music (Yoo, Kim, Kang and Choi, 2010).

CONCLUSIONS

In conclusion, this paper mostly concern about audio signal processing where the algorithm target on replication of the human listening ability on the machine. Although there is different method to solve BSS problem like principle component analysis (PCA), independent component analysis (ICA) and so on, the NMF approach has been consider as a best solution on solving BSS issue which has advantages such as producing a sparse representation of the data. The sparse presentation of data makes encoding easy to interpret due to use less active components which means the size of output will become less dense. In addition, the NMF leads to part-based decompositions. This will results NMF in obtaining higher accuracy of the output.With modifications in preprocessing stage, the algorithms propose can be used to wide range of applications such as in telecommunication and pattern recognition.

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REFERENCES

Hyvarinen, A. 1999. Fast and robust fixed-point algorithms for independent component analysis. IEEE Trans. Neural Netw., vol.10, no.3, pp.626–634.

Cichocki, A. and Unbehauen, R. 1996. Robust neural networks with on-line learning for blind identification and blind separation of sources. IEEE Trans. Circuits Syst. I: Fundam. Theory Appl., vol.43, no.11, pp.894–906.

Xiang, Y., Kui Ng, S. and Khanh Nguyen, V. 2010. Blind separation of mutually correlated sources using precoders. IEEE Trans. Neural Netw., vol.21, no.1, pp. 82-90.

Cardoso, J. and HvamLaheld, B. 1996. Equivariant adaptive source separation. IEEE Trans. Signal Process, vol. 44, no.12, pp. 3017-3030.

Yin, F., Mei, T. and Wang, J. 2007. Blind-source separation based on decorrelation and nonstationarity. IEEE Trans. Circuits Syst. I, vol.54, no.5, pp. 1150-1158.

Cichocki, A. and Amari, S. 2003. Adaptive Blind Signal and Image Processing. New York, USA, John Wiley.

Cichocki, A. and Amari, S. 2003. Adaptive Blind Signal and Image Processing - Learning Algorithm and Applications. John Wiley and Sons.

TjoaS. K. and Ray Liu K. J. 2010. Multiplicative Update Rules for Nonnegative Matrix Factorization with Co-

ARPN Journal of Engineering and Applied Sciences

Occurrence Constraints. Acoustics, Speech and Signal Processing, ICASSP, IEEE International Conference.

Cichocki, A., Zdunek, R.and Amari, S. 2006. New Algorithms for Non-Negative Matrix Factorization in Applications to Blind Source Separation. Acoustics, Speech and Signal Processing, ICASSP, IEEE International Conference, Vol. 5.

Lee, D. D.and Seung, H. S. 1999. Learning the parts of objects by nonnegative matrix factorization. Letters to Nature, vol.40, pp.788-791.

Ye, Z., Wenquan, Z., Guojin, W. and Yong, F. 2009. Blind Separation of Convolutive Mixed Source Signals by Using Robust Nonnegative Matrix Factorization. IEEE in Fifth International Conference on Natural Computation.

Lee, D.D. and Seung, H. S. 1997. Unsupervised learning by convex and conic coding. Proceedings of the Conference on Neural Information Processing Systems 9, pp. 515-521.

Lee, D. D. and Seung, H. S. 2001. Algorithms for non-negative matrix factorization. Conference of advances in neural information processing systems.

Schmidt, M. N. and Mørup, M. 2006. Nonnegative matrix factor 2-D deconvolution for blind single channel source separation. Journal of Independent Component Analysis and Blind Signal Separatio.

Lefevre,A., Bach, F. and Fevotte, C. 2011. Online Algorithms for Nonnegative Matrix Factorization with the Itakura-Saito Divergence. IEEE Workshop on Applications of Signal Processing to Audio and Acoustics October.

Févotte, C. and Idier, J. 2011. Algorithms for Nonnegative Matrix Factorization with the β-Divergence. Neural Computation, Vol. 23, issue 9.

Lin, C. and Hasting, E. 2013. Blind Source Separation of Heart and Lung Sounds Based on Nonnegative Matrix Factorization. IEEE Intelligent Signal Processing and Communications Systems (ISPACS), International Symposium.

Li, Y., Ho, K. C. and Popescu, M. 2014. Efficient Source Separation Algorithms for Acoustic Fall Detection Using a Microsoft Kinect. IEEE Transaction on Biomedical Engineering, Vol. 61, No. 3.

Lee, S. and Ha Park, S. 2012. Beamspace-Domain Multichannel Nonnegative Matrix Factorization for Audio Source Separation. IEEE Signal Processing Letters, Vol.19, No.1.

Grais, E. M. and Erdogan, H. 2011. Single Channel Speech Music Separation Using Nonnegative Matrix Factorization and Spectral Masks. IEEE Digital Signal Processing (DSP), 17th International Conference.

Sui, L., Zhang, X. Huang, J., Zhao, G. and Yang, Y. 2012. Speech Enhancement Based on Sparse Nonnegative Matrix Factorization with Priors. International Conference on Systems and Informatics (ICSAI).

Fan, H., Hung, J., lu, X., Wang, S. and Tsao, Y. 2014. Speech Enhancement Using Segmental Nonnegative Matrix Factorization. IEEE International Conference on Acoustic, Speech and Signal Processing (ICASSP).

Arjona Ram´ırez, M. 2014. Nonnegative Factorization of Sequences of Speech and Music Spectra. IEEE International Telecommunications Symposium (ITS).

Xu,G. and Wu, J. 2008. A Removal of Power Line Interference in Signal Based on Improved Nonnegative Matrix Factorization. IEEE International Conference on Computer Science and Information Technology.

Vincent, E., Gribonval, R. and Févotte, C. 2006. Performance Measurement in Blind Audio Source Separation. IEEE Transactions on Audio, Speech, and Language Processing, Vol.14, No.4.

Weninger, F., Lehmann, A. and Schuller, B. 2011. Openblissart: Design and Evaluation of a Research Toolkit for Blind Source Separation in Audio Recognition Tasks. IEEE International Conference, Acoustics, Speech and Signal Processing (ICASSP).

Yoo, J., Kim, M., Kang, K. and Choi, S. 2010. Nonnegative matrixpartial co-factorization for drum source separation. Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP), Austin, Texas, USA.

Yoo, J., Kim, M., Kang, K. and Choi, S. 2010. Blind Rhythmic Source Separation: Nonnegativity and Repeatability. IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP).