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Research Article

Research on Music Signal Processing Based on a Blind Source Separation Algorithm

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Abstract: The isolation of mixed music signals is beneficial to the extraction and identification of music signal features and to enhance music signal quality. This paper briefly introduced the mathematical model for separating blind source from mixed music signals and the traditional Independent Component Analysis (ICA) algorithm. The separation algorithm was optimized by the complex neural network. The traditional and optimized ICA algorithms were simulated in MATLAB software. It was found that the time-domain waveform of the signal isolated by the improved ICA-based separation algorithm was closer to the source signal. The similarity coefficient matrix, signal-to-interference ratio, performance index, and iteration time of the improved ICA-based algorithm was $\begin{bmatrix} 0.9999 & 0.0011 \\ 0.0022 & 0.9989 \end{bmatrix}$**, 62.3, 0.0011, and 0.87 s, respectively, which were all superior to the traditional ICA algorithm. The novelty of this paper is setting the initial iterative matrix of the ICA algorithm with the complex neural network.**

Keywords: ***Blind source separation; Complex neural network; Independent component analysis; Mixed music signal, Numerical filter, Short-time Fourier transform***

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1. Introduction

Sound signal recognition has more and more applications in everyday life, but the sound signals collected in real life are often mixed signals [1]. When performing instrument identification, melody extraction, and score transcription on music signals, the signals collected by sensors contain not only real source music signals but also signals of other components (noise or unwanted components) [2], especially noise, which can cause interference to the analysis and recognition of music signals. Therefore, before the formal analysis of music signals, different components need to be separated according to the demand, for example, separating the noise signal from music signals [3]. In practice, however, the music signal collected by the sensor is already mixed with noise, and the characteristics of both the source and noise signals are unknown. In such a case, the method to extract or restore the original signal by relying merely on the observed mixed signal is blind source separation. Kitamura *et al.* [4] proposed a statistical model to achieve high-quality blind source separation and verified the effectiveness of the model by experimental evaluation. Yang *et al.* [5] extracted human voice by combining a generalized short-time Fourier transform (STFT)-based technology with a filter bank. The experiment found that the method outperformed other methods. Muoz-Montoro *et al.* [6] used a multichannel non-negative matrix factorization (MNMF) system in source separation and verified its validity by experiments. This paper briefly introduced the mathematical model for blind source separation of mixed music signals and the traditional Independent Component Analysis (ICA) algorithm. The separation algorithm was optimized by the complex neural

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network. Simulation experiments were conducted in MATLAB software for both the traditional and improved ICA-based algorithms.

2. Blind Source Separation Algorithm for Music Signals

2.1. Mathematical Model

The purpose of blind source separation is to restore the mixed signals superimposed by multiple signals into the original signals that cannot be directly observed. Reasons for calling it a "blind source" are as follows. On the one hand, the original signal and other signals are superimposed so that they cannot be observed directly, and on the other hand, the superposition manner of the original signal and other signals is unknown [7]. The simplest way of separating mixed signals is to subtract the useless signal, but in the blind source separation, the difficulty lies in a priori information lacking, i.e., the relevant characteristic information of the useless signal. The mathematical model of the linear mixed signal [8] is:

$$\begin{cases} \mathbf{x} = \mathbf{H} \bullet \mathbf{s} \\ \mathbf{x} = (x_1, x_2, \cdots, x_n)^{\mathrm{T}} \\ \mathbf{s} = (s_1, s_2, \cdots, s_n)^{\mathrm{T}} \end{cases}, \tag{1}$$

where $\mathbf{x}$ is the set of observed signals, $\mathbf{s}$ stands for the set of independent source signals, and $\mathbf{H}$ is the hybrid matrix. When matrix $\mathbf{W}$ is the inverse matrix of hybrid matrix $\mathbf{H}$, then $\mathbf{s} = \mathbf{W} \cdot \mathbf{x}$, i.e., the set of source signals can be obtained by multiplying the observed hybrid signal set by matrix $\mathbf{W}$ [9].

2.2. ICA-based Blind Source Separation Algorithm Improved by a Complex Neural Network

It is seen from the above mathematical model of linear mixed signals that the focus of blind source separation for mixed music signals is to find matrix $\mathbf{W}$. The most commonly used method is ICA, which estimates matrix $\mathbf{W}$ according to the statistical characteristics of mixed signals. The steps are as follows.

① Equalization [10] and whitening preprocessing are performed on the observed music mixed signals.

② The initial matrix is set as $\mathbf{W}_p$, where $p = 0$.

③ The iterative calculation formula of matrix $\mathbf{W}$ is:

$$\begin{cases} \mathbf{W}_p^1 = E\left(\mathbf{x} g(\mathbf{W}_p^T \mathbf{x})\right) - E\left(g'(\mathbf{W}_p^T \mathbf{x})\right)\omega \\ \mathbf{W}_p^2 = \mathbf{W}_p^1 - \sum_{j=0}^{p-1} (\mathbf{W}_p^T \mathbf{W}_j) \mathbf{W}_j \\ \mathbf{W}_{p+1} = \dfrac{\mathbf{W}_p^2}{\left\| \mathbf{W}_p^2 \right\|} \end{cases}, \tag{2}$$

where $E(\cdot)$ is the mathematical expectation, $g(\cdot)$ is the nonlinear function, $g'(\cdot)$ is the first-order derivative of $g(\cdot)$, ω is the weight, and $\mathbf{W}_p^1$ and $\mathbf{W}_p^2$ are intermediate variables that transfer values [11].

④ Step ③ is repeated until $\mathbf{W}_p$ converges to stability or the number of iterations reaches the set number. $\mathbf{W}_p$ obtained after iteration is the desired matrix $\mathbf{W}$.

The traditional ICA algorithm utilizes the time-frequency signal characteristics but does not utilize the phase information of the music signal. To further upgrade the ICA algorithm [12], this paper takes advantage of the fact that the complex domain can better describe the music signal and the neural network can better approximate the real separation matrix to estimate the initial separation matrix using the complex neural network. Then, the ICA-based blind source separation algorithm uses this initial separation matrix for iterative computation [13]. Figure 1 shows the process of ICA-based blind source separation improved by the complex neural network.

① The mixed music signal is pre-processed by equalization and whitening. The time-frequency signal characteristics of the mixed music signal are obtained using STFT [14] and converted into data block $x(k,t)$ (k is the frequency point and t is the time point), as shown in Figure 2. Frames are used as time points in this paper, and there are b frames. $x(k,t)$ represents the complex value of the mixed signal at frequency point k and time t. Each frequency point corresponds to a separation matrix, then one data block contains k separation matrices.

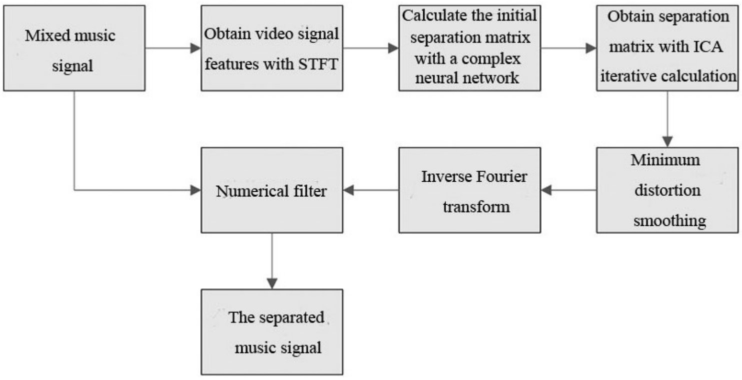

Figure 1. The process of ICA-based blind source separation improved by the complex neural network

$$\begin{bmatrix} x(k,t_1) & \cdots & x(k,t_{b-1}) & x(k,t_b) \\ x(k-1,t_1) & \cdots & x(k-1,t_{b-1}) & x(k-1,t_b) \\ \vdots & \vdots & \ddots & \vdots \\ x(1,t_1) & \cdots & x(1,t_{b-1}) & x(1,t_b) \end{bmatrix}$$

Figure 2. Time-frequency data blocks of the mixed music signal

② The data blocks of the mixed music signal are input into the complex neural network and calculated in the hidden layer with the following formula:

$$\begin{cases} z_t = \boldsymbol{\omega}\mathbf{h}_{t-1} + \mathbf{v}\mathbf{x}_t + b \\ \mathbf{h}_t = f_a(z_t) = \mathrm{Relu}(|z_t| + b)\dfrac{z_t}{|z_t|} \end{cases}, \quad (3)$$

where z_t is the output result under time t, $\mathbf{x}_t$ is the input under time t, $\mathbf{h}_t$ is the hidden node vector under time t, $\boldsymbol{\omega}$ is the weight matrix of the hidden node vector, $\mathbf{v}$ is the weight matrix of the input, and b is the bias term. If it is in the training phase, the calculated separation matrix is compared with the actual separation matrix of the data block labels to obtain its loss. If the loss exceeds the threshold [15], the weights in the hidden layer are reversely adjusted based on the loss, i.e., $\boldsymbol{\omega}$ and $\mathbf{v}$, and the separation matrix is recalculated until the loss converges and stabilizes in the range of the set threshold [16]. If in the use phase, the separation matrix is obtained by calculating according to equation (3).

③ The separation matrix calculated by the complex neural network is adopted as the initial matrix for the ICA iterative calculation, and the steps are consistent with the previous section and will not be repeated here.

④ After minimum smoothing treatment, the inverse Fourier transform is performed on the separation matrix obtained from the ICA iterative calculation to get the numerical filter [17].

⑤ The mixed music signal is filtered through the numerical filter of the separation matrix to obtain the blind source-separated music signal.

3. Simulation Experiments

3.1. Experimental Setup

Before conducting experiments on the blind source separation algorithm, the corresponding data set was prepared first, and the mixed music signals used for testing in this study were collected in a recording room. The scene arrangement in the recording room [18] is shown in Figure 3. The room had a size of 3 m × 5 m. Two source signals were set on the left side of the room, and the distance between the two source signals was 1 m; three microphones were set on the right for collecting the music signals mixed by the two source signals, the distance between the microphones was 1 m, and the source signals were 3 m away from the microphones. The music signals played by the source signals were all mono. The sampling frequency of the microphones was 16 kHz, and the collection time was 1 s each time. Three mixed signals collected by the three microphones each time were set as a group, and 10000 groups of mixed music signals were collected. Among the 10000 groups, 7000 groups were used as training data, and 3000 groups were used as test data. Observation signals of the three microphones at one time of sampling are shown in Figure 4.

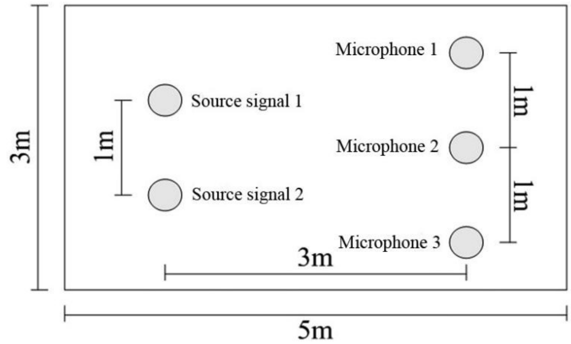

Figure 3. Experimental scene arrangement for mixed music signal acquisition

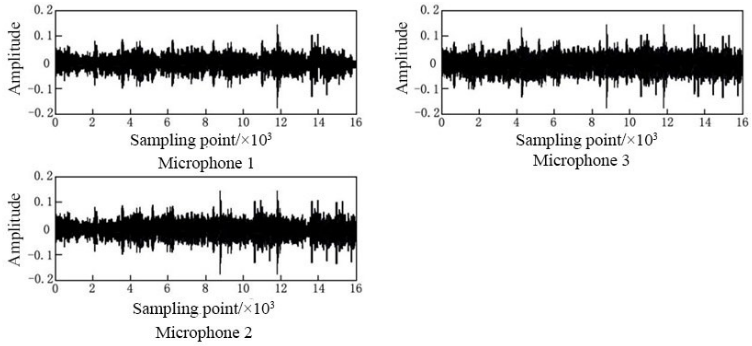

Figure 4. Observation signals of the three microphones at one time of sampling

To verify the performance of the complex neural network-improved ICA algorithm, it was compared with the traditional ICA algorithm. The traditional ICA algorithm used the statistical features of the mixed music signal observed by the microphone to iterate the separation matrix. The improved ICA algorithm used a complex neural network to initially estimate the separation matrix and then iterated on the estimated separation matrix to obtain the final separation matrix to separate the mixed signals. The complex neural network was trained with the training data before it was formally used, and its relevant parameters are as follows. Subframe windowing was performed on the collected mixed signals using the Hamming window [19] according to time, and the length of the Hamming window was 4096 sampling points. The inter-frame overlap rate was 75%, the Relu function was used in the in hidden layer, the learning step length was 0.1, and the maximum number of iterations was 2000.

3.2. Evaluation Criteria

The similarity coefficient [20] in the similarity coefficient matrix is calculated:

$$r_{i,j} = \frac{\left|\sum_{i,j=1}^{n} y_i s_j\right|}{\sqrt{\sum_{i=1}^{n} y_i^2 \sum_{j=1}^{n} s_j^2}}, \tag{4}$$

where y_i is the i-th signal after the blind source separation, s_j represents the j-th source signal before mixing, n refers to the number of signal paths (two source signals are used in this paper, then there are two signal paths before mixing and two signal paths after separation), and $r_{i,j}$ is the similarity coefficient of y_i and s_j (the closer the value is to 1, the more similar they are). When the similarity coefficient matrix and the unit matrix are closer, the separation effect of the algorithm is better.

The calculation formula for signal-to-interference ratio (SIR) is:

$$SIR = 10\log_{10}\frac{E(s_i^2)}{E((y_i - s_i)^2)}, \tag{5}$$

where y_i and s_i are the separated signal and the corresponding source signal. A larger SIR means a better separation effect.

The performance index is calculated by the following formula:

$$PI = \frac{\sum_{i=1}^{n}\left(\left(\sum_{k=1}^{n}\frac{|g_{ik}|}{\max_j |g_{ij}|}-1\right)+\left(\sum_{k=1}^{n}\frac{|g_{ki}|}{\max_j |g_{ji}|}-1\right)\right)}{n(n-1)}, \tag{6}$$

where the global matrix is $\mathbf{G}=\mathbf{W}\times\mathbf{H}$, g_{ik} is the element of the i-th row and k-th column, g_{ki} is the element of the k-th row and i-th column, $\max_j |g_{ij}|$ is the largest absolute value in the i-th row in $\mathbf{G}$, and $\max_j |g_{ji}|$ is the largest absolute value in the i-th column. Performance index PI is a non-negative number; the smaller its value is, the better the separation is.

3.3. Experimental Results

Only the two source signals under the sampling in Figure 4 and the signals after separations by traditional ICA and improved ICA algorithms are shown in Figure 5 because of the limited space. The two signals separated by the traditional ICA had obvious interference compared with the source signals, resulting in a large gap between the time domain waveform of the separated and source signals, but the two signals separated by the complex neural network-improved ICA had less interference compared with the source signals.

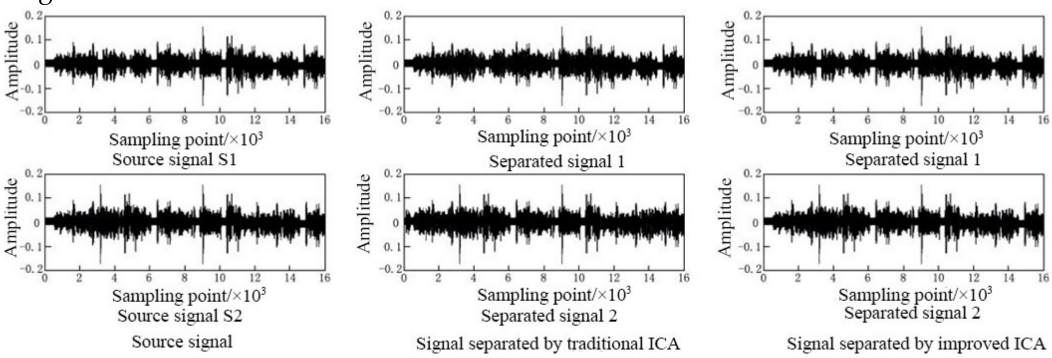

Figure 5. Source signals and the signals separated by traditional ICA and improved ICA algorithms

Table 1. Similarity coefficient matrix, SIR, performance index and average iteration time of two algorithms

	Traditional ICA-based separation	Improved ICA-based separation
Similarity coefficient matrix	$\begin{bmatrix}0.8655 & 0.0111\\ 0.0212 & 0.8897\end{bmatrix}$	$\begin{bmatrix}0.9999 & 0.0011\\ 0.0022 & 0.9989\end{bmatrix}$
Average iteration time/s	1.89	0.87
SIR	52.4	62.3
Performance index	0.0043	0.0011

In this paper, 3000 groups of mixed music signals were used as testing data for testing the non-improved and improved ICA-based blind source separation algorithms. The similarity coefficient matrix was obtained after calculating based on every group of separated mixed music signals and the source signal, but it is impossible to show all the similarity coefficient matrices of the test set due to the limitation of space. Therefore, we finally chose the average value of the similarity coefficient matrices to measure the two separation algorithms. In addition, as the traditional ICA-based blind source separation algorithm did not rank the separated signals that are output when the mixed signals are separated, it may lead to a mismatch between the number of source signal paths and separated signal paths, i.e., the sorting of the separated signals obtained from different groups of test data was not uniform, which affected the calculation of the average value of the similarity coefficient matrices. As to the improved separation algorithm, the training set label had already included the sorting method during supervised training. Therefore, the improved separation algorithm did not need to worry about the ranking of the separation signals. Thus, in this paper, a uniform ranking of the separation signals was performed before calculating the similarity coefficient matrix, and the average value and the average time taken for the iterative calculation are shown in Table 1. The average time required for iterative computation of the separation matrix was 1.89 s for the traditional ICA algorithm and 0.87 s for the improved ICA algorithm. It was found from the comparison of the average similarity coefficient matrix between the two separation algorithms that the similarity coefficient matrix of the improved ICA-based blind source separation algorithm was close to the unit matrix, every row and column had one and only one element closer to 1, and the other elements were closer to 0; the similarity coefficient matrix of the traditional ICA-based blind source separation algorithm had the same trend, but its approaching degree was not as high as the improved ICA blind source separation algorithm. In addition, the average SIR and performance index of the traditional ICA-based separation algorithm were 52.4 and 0.0043, while the average SIR and performance index of the improved ICA-based separation algorithm were 62.3 and 0.0011. It was found from the above experimental results that the similarity coefficient matrix, SIR, performance index, and the average iteration time all showed that the improved ICA-based blind source separation algorithm had a better mixed signal separation effect and higher separation efficiency.

4. Conclusion

The traditional blind source separation algorithm was improved by a complex neural network, and traditional and improved ICA-based blind source separation algorithm were simulated in MATLAB software. The obtained results are shown below. The time domain waveform of the signal separated by the traditional ICA-based separation algorithm was significantly different from the source signal, while the time domain waveform of the signal separated by the improved ICA-based separation algorithm was slightly different from the source signal. The similarity coefficient matrix of the improved ICA-based separation algorithm was closer to the unit matrix than the traditional algorithm. The SIR, performance index and average iteration time of the traditional ICA-based separation algorithm were 52.4, 0.0043 and 1.89 s; the SIR, performance index and average iteration time of the improved ICA-based separation algorithm were 62.3, 0.0011 and 0.87 s.

References

[1] Yangyang Deng, Yuehui Wang, Yiqing Zhang, Axin Du and Jianguo Liu, "The realization of a wide-angle voice transmission non-line-of-sight ultraviolet communication system", *Journal of Semiconductors*, ISSN: 1674-4926, Vol. 42, No. 9, pp. 37-42, 17th September 2021, Published by IOP Publishing, DOI: 10.1088/1674-4926/42/9/092301, Available: https://iopscience.iop.org/article/10.1088/1674-4926/42/9/092301.

[2] Pengfei Xu, Yinjie Jia and Mingxin Jiang, "Blind audio source separation based on a new system model and the Savitzky-Golay filter", *Journal of Electrical Engineering-elektrotechnicky Casopis*, Print ISSN: 1335-3632, Online ISSN: 1339-309X, Vol. 72, No. 3, pp. 208-212, 2021, Published by Sciendo, DOI: 10.2478/JEE-2021-0029, Available: https://www.xueshufan.com/publication/3177540365.

[3] Mahdi Khosravy, Neeraj Gupta, Nilesh Patel, Nilanjan Dey, Naoko Nitta *et al.*, "Probabilistic Stone's Blind Source Separation with application to channel estimation and multi-node identification in MIMO IoT green communication and multimedia systems", *Computer Communications*, Online ISSN: 0140-3664, pp. 423-433, Vol. 157, 1st May 2020, Published by Elsevier B.V., DOI: 10.1016/j.comcom.2020.04.042, Available: https://www.sciencedirect.com/science/article/abs/pii/S0140366420302516.

[4] Daichi Kitamura, Shinichi Mogami, Yoshiki Mitsui, Norihiro Takamune, Hiroshi Saruwatari *et al.*, "Generalized independent low-rank matrix analysis using heavy-tailed distributions for blind source separation", *Eurasip Journal on Advances in Signal Processing*, Online ISSN: 1687-6180, pp. 28, Vol. 2018, No. 1, 2nd May 2018, Published by Springer Nature, DOI: 10.1186/s13634-018-0549-5, Available: https://link.springer.com/article/10.1186/s13634-018-0549-5.

[5] Ning Yang, Muhammad Usman, Xiangjian He, Mian Ahmad Jan and Liming Zhang, "Time-Frequency Filter Bank: A Simple Approach for Audio and Music Separation", *IEEE Access*, Online ISSN: ISSN: 2169-3536, pp. 27114-27125, Vol. 5, 10th October 2017, Published by IEEE, DOI: 10.1109/ACCESS.2017.2761741, Available: https://ieeexplore.ieee.org/document/8063868/references#references.

[6] Antonio Jesús Muñoz Montoro, J.J. Carabias, Raquel Cortina, Sebastian Garcia Galan and Josr Ranilla, "Parallel multichannel blind source separation using a spatial covariance model and nonnegative matrix factorization", *The Journal of Supercomputing*, Print ISSN: 0920-8542, Online ISSN: 1573-0484, pp. 12143-12156, Vol. 77, 6th April 2021, DOI: 10.1007/s11227-021-03771-y, Available: https://link.springer.com/article/10.1007/s11227-021-03771-y.

[7] Ozge Canli Usta and Hatice Dogan, "Speech protected noise cancellation system in noise dominated environments", *Applied Acoustics*, ISSN: 0003-682X, pp. 1-10, Vol. 189, 2022, DOI: 10.1016/j.apacoust.2021.108577, Available: https://www.sciencedirect.com/science/article/abs/pii/S0003682X2100671X.

[8] Chenghong Yang and Hongjuan Zhang, "Singing voice separation with pre-learned dictionary and reconstructed voice spectrogram", *Neural Computing and Applications*, Print ISSN: 0941-0643, E-ISSN: 1433-3058, Vol. 32, No. 5, pp. 3311-3322, 6th October 2018, Published by Springer Nature, DOI: 10.1007/s00521-018-3757-x, Available: https://link.springer.com/article/10.1007/s00521-018-3757-x#citeas.

[9] Yichen Zhao, Weihong Fu, Chunhua Zhou and Yongyuan Liu, "Energy Correlation Permutation Algorithm of Frequency-Domain Blind Source Separation Based on Frequency Bins Correction", *Wireless Personal Communications*, Print ISSN: 0929-6212, Online ISSN: 1572-834X, pp. 1-16, Vol. 120, No. 2, 23rd April 2021, Published by Springer Nature, DOI: 10.1007/s11277-021-08533-w, Available: https://link.springer.com/article/10.1007/s11277-021-08533-w?utm_medium=affiliate&utm_content=meta.

[10] Hua Yang, Hang Zhang, Jiang Zhang and Liu Yang, "An anti-repeater-jamming approach based on blind source separation for the downlink of satellite communication systems", *International Journal of Satellite Communications and Networking*, Print ISSN: 1542-0973, E-ISSN: 1542-0981, Vol. 37, No. 6, 11th December 2018, Published by John Wiley and Sons Ltd, DOI: 10.1002/sat.1294, Available: https://onlinelibrary.wiley.com/doi/10.1002/sat.1294.

[11] Rajendra Mohite and Prof Onkar singh Singh Lamba, "Blind Source Separation Survey", *International Journal of Scientific & Technology Research*, ISSN 2277-8616, pp. 340-344, Vol. 8, No. 11, November 2019, Published by IJSTR, Available: http://www.ijstr.org/final-print/nov2019/Blind-Source-Separation-Survey.pdf.

[12] Chuanchuan Wang and Rui Jia, "A Source Signal Recovery Method for Underdetermined Blind Source Separation based on Shortest Path", *Applied Computational Electromagnetics Society Journal*, ISSN: 1054-4887, pp. 406-414, Vol. 35, No. 4, 2020, Published by Applied Computational Electromagnetics Society (ACES), Inc., Available: https://www.nstl.gov.cn/paper_detail.html?id=33a3ea855258108b7b53d727e5d9a5b5.

[13] Muhammad Umair Khan and Tania Habib, "Concurrent speakers localization using blind source separation and microphone array geometry", *Multidimensional Systems and Signal Processing*, Print ISSN: 0923-6082, Online ISSN: 1573-0824, pp. 1159-1184, Vol. 2021, No. 2, 9th May 2021, Published by Springer Nature, DOI: 10.1007/s11045-021-00776-x, Available: https://link.springer.com/article/10.1007/s11045-021-00776-x.

[14] Jiai He, Wei Chen and Yuxiao Song, "Single Channel Blind Source Separation Under Deep Recurrent Neural Network", *Wireless Personal Communications*, Print ISSN: 0929-6212, Online ISSN: 1572-834X, pp. 1277-1289, Vol. 115, No. 1, 7th July 2020, Published by Springer Nature, DOI: 10.1007/s11277-020-07624-4, Available: https://link.springer.com/article/10.1007/s11277-020-07624-4.

[15] Renke He, Yanhua Long, Yijie Li and Jiaen Liang, "Mask-based blind source separation and MVDR beamforming in ASR", *International Journal of Speech Technology*, Print ISSN: 1381-2416, Online ISSN: 1572-8110, pp. 133-140, Vol. 23, No. 8, 20th December 2019, Published by Springer Nature, DOI: 10.1007/s10772-019-09666-x, Available: https://link.springer.com/article/10.1007/s10772-019-09666-x.

[16] Rahima Henni, Mustapha Djebari and Djendi Mohamed, "A new joint noise reduction and echo suppression system based on FBSS and automatic voice activity detector", *Applied Acoustics*, Print ISSN: 0003-682X, E-ISSN: 1872-910X, Vol. 168, November 2020, Published by Elsevier, DOI: 10.1016/j.apacoust.2020.107444, Available: https://www.sciencedirect.com/science/article/abs/pii/S0003682X2030548X.

[17] Kan Hong, "Non-contact physical stress measurement using thermal imaging and blind source separation", *Optical Review*, Print ISSN: 1340-6000, Online ISSN: 1349-9432, pp. 116-125, Vol. 27, No. 2, 3rd January 2020, Published by Springer Verlag, DOI: 10.1007/s10043-019-00573-9, Available: https://link.springer.com/article/10.1007/s10043-019-00573-9.

[18] Louis Dermagne, Philippe-Aubert Gauthier and Alain Berry, "Ambisonics and blind source separation in virtual acoustics: Sound field reproduction of separated sources", *The Journal of the Acoustical Society of America*, Print ISSN: 0001-4966, pp. 2794-2794, Vol. 148, No. 4, 3rd December 2020, Published by Acoustical Society of America, DOI: 10.1121/1.5147776, Available: https://asa.scitation.org/doi/10.1121/1.5147776.

[19] Luay Taha and Esam Abdel-Raheem, "A Computationally Efficient Blind Source Extraction Using Idempotent Transformation Matrix", *Circuits, systems, and signal processing: CSSP*, Print ISSN: 0278-081X, Online ISSN: 1531-5878, pp. 2245-2265, Vol. 38, No. 4, 12nd October 2018, Published by Springer Nature, DOI: 10.1007/s00034-018-0961-y, Available: https://link.springer.com/article/10.1007/s00034-018-0961-y.

[20] Qiao Zhou, Jie-Peng Yao, Jin-Hai Li, Zhong-Yi Wang and Lan Huang, "A smart universal single-channel blind source separation method and applications", *Multidimensional Systems and Signal Processing*, Print ISSN: 0923-6082, E-ISSN: 1573-0824, pp. 1-27, 13th August 2022, Published by Springer US, DOI: doi.org/10.1007/s11045-022-00843-x, Available: https://link.springer.com/article/10.1007/s11045-022-00843-x.