31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Detecting Changes in Respiratory Patterns in High Frequency Chest Compression Therapy by Single-Channel Blind Source Separation

Xiaoming Zhu, Keshab K. Parhi, *Fellow, IEEE* and Warren J. Warwick, M.D.

***Abstract*— High Frequency Chest Compression (HFCC) is used as a method to remove the mucus in the airway for Cystic Fibrosis (CF) patients. As the characteristics of the tracheal sound reflect the conditions of airways, in this paper, we propose a novel method to evaluate the respiratory patterns in HFCC therapy by using single channel tracheal sounds only. The difficulty of analyzing tracheal sounds lies in that it has a wider frequency band than the air flow at the mouth, and is always corrupted by other biomedical signals and noises. During HFCC therapy, the tracheal sound is also affected by the HFCC machine noise. For this reason, it is difficult to extract respiratory patterns and other related features by traditional filtering techniques. In this paper, we demonstrate use of single-channel independent component analysis to extract respiratory patterns from the tracheal sounds before, during and after HFCC therapy, and use basis features in the tracheal sound to detect the change in respiratory patterns.**

I. INTRODUCTION

High Frequency Chest Compression (HFCC) has been one of the most effective therapeutic methods to assist in clearing mucus-associated microorganisms from the infected respiratory systems of Cystic Fibrosis (CF) patients or Chronic Obstructive Pulmonary Disease (COPD) patients. To evaluate the effect of HFCC therapy, numerous methods have been proposed such as measuring the amount of induced air flow at the mouth, the amount of cleared dry or wet sputum, and the amount of gas exchange rate of N_2, O_2 and CO_2 during the expiration and inspiration [1]–[4]. In addition, HFCC effects on the heart rate variability, cardio-respiratory synchronization and sinus arrhythmia during HFCC therapy have been presented in [5] [6]. As we believe that the frequency or intensity of tracheal sounds is closely related to the change of dimensions of airways that result from the inflammation or accumulated mucus, it is important to analyze the tracheal sound directly to identify positive or negative changes associated with HFCC therapy.

The advantages of analyzing tracheal sounds are obvious. First, respiratory patterns can be extracted from the tracheal sound. There is no need to measure the air flow at the mouth to identify the expiration and inspiration periods. Second, features can be extracted from the tracheal sound that are related to the dimensions of airways. Future automatic diagnosis based on these features becomes possible. Third, monitoring changes of pulmonary function by tracheal sound is realizable. We may only use one stethoscope to track the long-term change of airways for CF patients. However, it is not an easy task to analyze tracheal sound directly. Tracheal sound is nonstationary and often a mixture of other biomedical signals and environmental noises. Therefore, it has a much wider frequency band than air flow at the mouth. By traditional filtering, it is difficult to extract meaningful frequency band from the tracheal sound. For this reason, we propose to use single-channel independent component analysis algorithm [7] to extract independent components (ICs) from the tracheal sound and identify respiratory patterns from extracted ICs, and use basis features [8] to detect changes of respiratory patterns in the tracheal sound.

Xiaoming Zhu is with Department of Electrical and Computer Engineering, University of Minnesota, 200 Union St SE, Minneapolis, MN, 55414. Email: xmzhu@umn.edu

Keshab K. Parhi is with the Department of Electrical and Computer Engineering, University of Minnesota, 200 Union St SE, Minneapolis, MN, 55414. Email: parhi@umn.edu

Warren J. Warwick is with the Department of Pediatrics, University of Minnesota, 516 Delaware St SE, Minneapolis, MN, 55414. Email: warwi001@umn.edu

II. PROPOSED METHOD

Blind source separation [9] is a signal processing technique that is used to extract unknown source signals from observed mixtures without any knowledge of the sources and how they are mixed. In this paper, we assume that the single channel tracheal sound consists of up to N sources

$$x(t) = a_1 s_1(t) + a_2 s_2(t) + \cdots + a_N s_N(t). \qquad (1)$$

where $x(t)$ is the recorded tracheal sound, $\{a_i\}_{i=1}^N$ are mixing coefficients and $\{s_i(t)\}_{i=1}^N$ are N source signals. The assumption of this problem is that each source signal is independent of each other[1]. Based on this assumption, we can use independent component analysis [10] to solve it. In Equation (1), we have N sources, but only one mixture. The problem is ill-defined. A pseudo mixture vector [11] has to be built such that there are as many mixtures as sources. The pseudo mixture vector is given by

$$\mathbf{x}(t) = [x(t), x(t-\tau), \cdots, x(t-(N-1)\tau)]^T \qquad (2)$$

where τ is the delay element. Equation (1) can be written as

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) = \sum_{i=1}^{N} \mathbf{a}_i s_i(t) + \mathbf{n}(t). \qquad (3)$$

where $\mathbf{A} = [\mathbf{a}_1, \cdots, \mathbf{a}_N]$ is an unknown $(N \times N)$ mixing matrix with full rank, $\mathbf{s}(t) = [s_1(t), \cdots, s_N(t)]^T$ is the source vector, and $\mathbf{n}(t)$ is the additive Gaussian white noise vector. Column vectors $\{\mathbf{a}_i\}_{i=1}^N$ are known as basis features. Standard ICA algorithms such as fast ICA [12], infomax

[1]For this reason, we use source signal and independent component interchangeably.

978-1-4244-3296-7/09/$25.00 ©2009 IEEE

[13], maximum-likelihood [14] and complexity pursuit [15] can be applied to estimate the unmixing matrix $\mathbf{W} = \mathbf{A}^{-1}$ such that the estimated sources are

$$\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t). \tag{4}$$

In this paper, fast ICA algorithm will be used to extract independent components (ICs) from the single channel tracheal sound because it is fast and robust. After being trained, the mixing matrix $\mathbf{A}$ and the unmixing matrix $\mathbf{W}$ are pattern-dependent which means that $\mathbf{W}$ can only decompose the tracheal sound with the same pattern as the training data into ICs, whereas other tracheal sounds with different patterns cannot be decomposed into ICs, but only into correlated components. Based on this property, two test functions J_1 and J_2 are derived to detect changes in respiratory patterns by the tracheal sound.

A. Estimate Mixing & Unmixing Matrix

Fast ICA is based on the fourth moment or kurtosis of the signals, defined as

$$K(s) = \frac{E[s^4]}{(E[s^2])^2} - 3. \tag{5}$$

where s is a zero-mean random variable. According to the analysis in [10], a signal extracted from the mixtures that has the maximum kurtosis is considered as an independent component (IC). Thus the problem of Equation (4) becomes an optimization problem of Equation (5). This is a sequential method that only one IC is extracted at one time. Also, pre-whitening by singular value decomposition (SVD) is required for fast computation purpose. After one IC is extracted, Gram-Schmidt orthogonalization (GSO) is performed to eliminate the effect of the extracted IC on the mixtures. After all ICs are extracted, Cycle-Spinning is used to reduce blocking artifacts in the ICs [7] [16].

Assume $\mathbf{x}(t)$ is zero-mean. Let $\mathbf{x} = [\mathbf{x}(0), \cdots, \mathbf{x}(T)]$ where T is the duration of time, and $\mathbf{w}_i^T$ is the i^{th} row vector of $\mathbf{W}$ extracting the i^{th} source signal $s_i(t)$. Note that the superscript T represents the transpose operation. By SVD,

$$\mathbf{x}^T = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^T \tag{6}$$

where $\mathbf{U}$ is a $(T \times N)$ orthonormal matrix of eigenvectors, $\mathbf{V}$ is an $(N \times N)$ orthonormal matrix of eigenvectors, and $\mathbf{\Lambda}$ is an $(N \times N)$ diagonal matrix of singular values. We define $\mathbf{z}^T \triangleq \mathbf{U}$, where $\mathbf{z}$ is a set of $(N \times T)$ whitened mixtures and $\mathbf{z}(t)$ is the t^{th} column of $\mathbf{z}$. After whitening, fast ICA can be applied on $\mathbf{z}(t)$. The table of algorithm 1 summarizes the fast ICA algorithm.

As proved in [7], the separable condition for single-channel independent component analysis is that ICs should be spectrally disjoint. According to our experience, as the tracheal sound is recorded around the neck, the main source signals in the mixture are the tracheal sound, the pulse sound, device noise, electric line noise and environment noise. Other biomedical signals are weak in the mixture. As tracheal sound is typically of lower frequency than the others, it can be separated from the mixture.

Algorithm 1 Training unmixing matrix $\mathbf{W}$

1: **for** $i = 1$ to N **do**
2: Get $\mathbf{z}(t)$ by Equation (6).
3: $\mathbf{w}_{old}$=$\mathbf{w}_i$
4: $\triangle_{\mathbf{w}_i} = E[\mathbf{z}(t)(\mathbf{w}_i^T\mathbf{z}(t))^3]$
5: $\mathbf{w}_i \Leftarrow \mathbf{w}_i + \mu \triangle_{\mathbf{w}_i}$
6: $\mathbf{w}_i \Leftarrow \mathbf{w}_i / \|\mathbf{w}_i\|$
7: **if** $|\mathbf{w}_{old}^T\mathbf{w}_i - 1| > \varepsilon$ **then**
8: Go back to step 3.
9: **end if**
10: $\hat{s}_i(t) = \mathbf{w}_i^T\mathbf{z}(t)$
11: $\mathbf{x}(t) \Leftarrow \mathbf{x}(t) - E[\hat{s}_i(t)\mathbf{x}(t)]\hat{s}_i(t)/E[\hat{s}_i^2(t)]$
12: $\mathbf{w}_i \Leftarrow \mathbf{V}\mathbf{\Lambda}^{-1}\mathbf{w}_i$
13: **end for**
14: $\mathbf{A} = \mathbf{W}^{-1}$

B. Basis Features

Basis features are defined as the column vectors $\{\mathbf{a}_i\}_{i=1}^N$ and have been successfully applied in speech recognition [8]. Equation (3) shows that $\{\mathbf{a}_i\}_{i=1}^N$ uniquely relate $\mathbf{x}(t)$ and $\mathbf{s}(t)$. After the unmixing matrix $\mathbf{W}$ is trained, the mixing matrix $\mathbf{A}$ is also uniquely determined due to a one-to-one correspondence. This exactly means that $\{\mathbf{a}_i\}_{i=1}^N$ can be used as a valid feature set for detecting changes in respiratory patterns by tracheal sounds. Once the respiratory pattern in the tracheal sound has been changed, the corresponding basis features will be changed accordingly. In the rest of the description, we interchangeably use $\mathbf{A}$ and $\mathbf{W}$ as the feature since they are uniquely related to each other.

We propose two test functions J_1 and J_2 to detect changes in respiratory patterns. Both test functions utilize the fact that $\mathbf{W}$ can only decompose the tracheal sound with the same respiratory patterns as the training data into ICs. These test functions are defined as

$$J_1 = \|E[\hat{\mathbf{s}}(t)\hat{\mathbf{s}}^T(t)] - \mathbf{I}\|_p \tag{7}$$

$$= \|\mathbf{W}E[\mathbf{x}(t)\mathbf{x}^T(t)]\mathbf{W}^T - \mathbf{I}\|_p \tag{8}$$

$$J_2 = \sum_{i=1}^{N} \log\{\frac{E[(\hat{s}_i^e(t) - \hat{s}_i(t))^2]}{E[(\hat{s}_i(t))^2]}\} \tag{9}$$

$$= \sum_{i=1}^{N} \log\{\frac{E[(\mathbf{w}_i^T\mathbf{x}^e(t) - \mathbf{w}_i^T\mathbf{x}(t))^2]}{E[(\mathbf{w}_i^T\mathbf{x}(t))^2]}\} \tag{10}$$

where $\|\cdot\|_p$ is the entrywise p-norm defined as $\|\mathbf{A}\|_p \triangleq (\sum_{i=1}^N \sum_{j=1}^N |a_{ij}|^p)^{1/p}$, $\hat{s}_i^e(t)$ and $\mathbf{x}^e(t)$ are the predicted values of $\hat{s}_i(t)$ and $\mathbf{x}(t)$, respectively. Moving average filter can be used as a simple linear predictor in Equation (10).

Test function J_1 measures the correlation among the extracted sources $\{\hat{s}_i(t)\}_{i=1}^N$. The value of the test function is minimized if the feature set $\{\mathbf{a}_i\}_{i=1}^N$ (or equivalently $\mathbf{W}$) belongs to the input signal $\mathbf{x}(t)$. In this case, the extracted signals are the ICs. Test function J_2 measures the temporal complexity [15] of the extracted sources. Temporal complexity is a parameter that measures the complexity of the signal $\{\hat{s}_i(t)\}_{i=1}^N$ in the time domain. The assumption of

using temporal complexity is that if the extracted signals are real source signals, they should be less complex than mixtures. In other words, if the feature set $\{\mathbf{a}_i\}_{i=1}^N$ belongs to $\mathbf{x}$(t), the value of J_2 should be minimized. Test function J_2 is more robust than J_1 in that if $\mathbf{x}(t)$ is a temporally whitened signal, J_1 will always generate the same value (minimum for all respiratory patterns) because in this case $E[\mathbf{x}(t)\mathbf{x}^T(t)] = \mathbf{I}$. Generally, in our research, these two test functions have almost the same performance to detect changes in the respiratory patterns. They can be combined to achieve even better performance.

C. Data Acquisition

We measured the tracheal sounds from a female CF patient 10 minutes before, during, and 10 minutes after HFCC therapy. The ICS HFCC system (developed by Respiratory Technologies Inc., St. Paul, MN) induces triangle waveform at the mouth. This system has 10 pressure settings from 10% to 100% of maximum pressure with a frequency range of 5-30Hz. In this paper, we selected 5Hz and 100% of maximum pressure setting with a pressure range of 6-31 *mmHg* and mean 18.5 *mmHg*. The duration of HFCC therapy was about half an hour. The tracheal sounds were recorded by 3M Littman Electronic Stethoscope 4000 with a sampling frequency of 8*KHz*. The duration of each tracheal sound is 8*s*, which is limited by the device. For simplicity, we use BHTS, DHTS and AHTS to denote the tracheal sound from the female CF patient before, during and after HFCC therapy, respectively.

III. Experimental Results

A. Extract Respiratory Patterns from Tracheal Sound

In this experiment, we assume there are 64 ICs in the tracheal sound. If redundant basis features show up, this means that we have assumed too many ICs. We can either use Principal Component Analysis [10] or *k*-means algorithm to reduce or group redundant basis features, and then use Equation (4) to extract reduced ICs. For purposes of identifying respiratory patterns and detecting changes, even if we do nothing on redundant features, it will not affect our results. Fig. 1 shows three tracheal sounds, BHTS, DHTS and AHTS. In these three figures, the respiratory patterns are difficult to estimate. Fig. 2 shows one of the ICs from each of the tracheal sounds. In the top figure, we can estimate that before HFCC therapy, the inspiration period is about 2.3*s* and the expiration period is about 3*s*. In the middle figure, after HFCC therapy, the inspiration period is still about 2.3s, but the expiratory period is changed to 2.5*s*. The bottom figure shows the induced respiratory pattern by HFCC. The respiratory pattern is modulated by the frequency of 5*Hz*, which is the HFCC working frequency, and its envelope shows the real respiratory pattern. We can estimate that the inspiration period is about 2.2*s* and the expiration period is about 2.8*s*.

Fig. 3 and Fig. 4 show the 64 basis features of the tracheal sound BHTS and AHTS. The basis features of BHTS are almost all low frequency features, while those of AHTS have some high frequency components. This is because the mucus in the airway has been cleared by HFCC therapy. The basis features for these two tracheal sounds are quite different, which indicates the respiratory patterns have changed after HFCC therapy. Therefore, test functions J_1 and J_2 can be used to detect the changes.

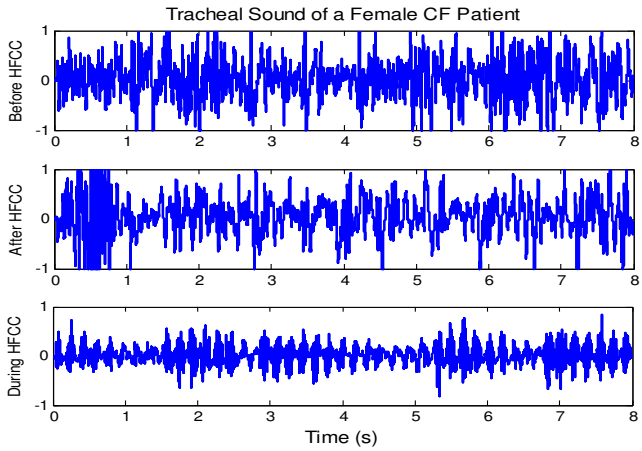

Fig. 1. Tracheal sounds BHTS, AHTS and DHTS.

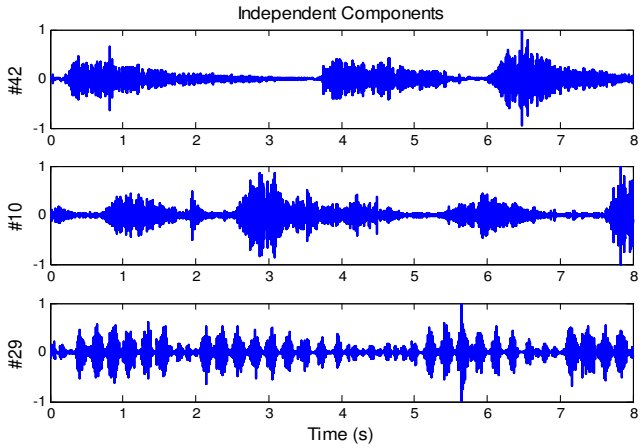

Fig. 2. ICs extracted from the tracheal sounds. Top: The 42nd IC from BHTS; Middle: The 10th IC from AHTS; Bottom: The 29th IC from DHTS.

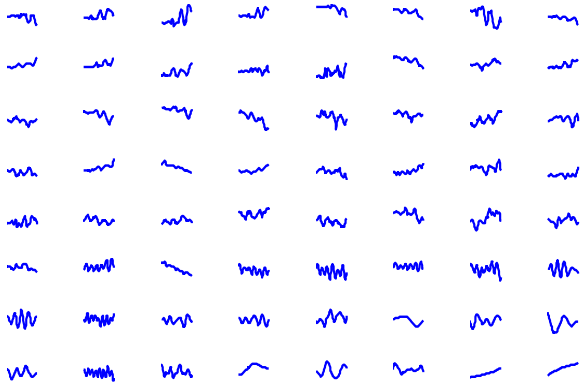

Fig. 3. Complete 64 basis features of BHTS.

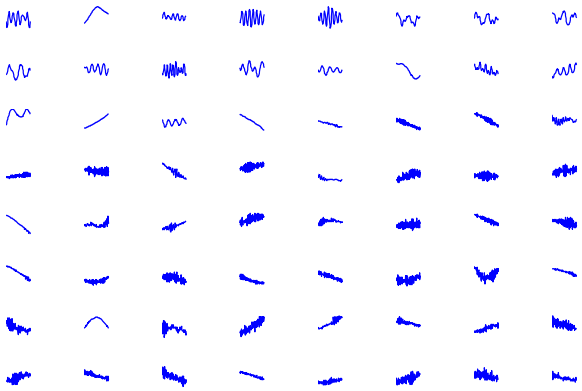

Fig. 4. Complete 64 basis features of AHTS.

B. Detect Changes in Respiratory Patterns

In this experiment, due to the limitation of the stethoscope we use, we construct an artificial tracheal sound shown in Fig. 5. The first half of the tracheal sound is from BHTS and the second half from AHTS. The respiratory pattern is changed in the middle (around 8s). The entire artificial tracheal sound contains 4 respiratory cycles, two in each half. The unmixing matrix $\mathbf{W}$ is trained by only one respiratory cycle (about 32000 samples) either from BHTS or from AHTS. Then the tracheal sound is segmented into frames of 6400 samples. Each frame is used to generate a value for two test functions. The results are shown in Fig. 6. In the left two figures, $\mathbf{W}$ is trained by BHTS and in the right two, $\mathbf{W}$ is trained by AHTS. The test functions are minimized by the respiratory pattern in the training data. We can see that both test functions detect the changes of respiratory pattern at the 11th frame which is exactly the place where the respiratory pattern is changed in the artificial tracheal sound. This experiment verifies both the validity of basis features and two proposed test functions.

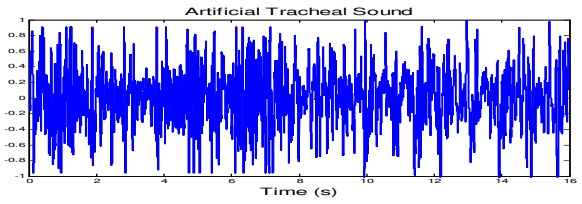

Fig. 5. An artificial tracheal sound. The first half is from BHTS and the second half is from AHTS.

IV. Conclusion

This paper proposes a novel method to detect the changes in respiratory patterns by HFCC therapy based on single-channel independent component analysis. The tracheal sound is decomposed into different independent components. Result shows that it is much easier to identify the respiratory pattern in the ICs than in the original tracheal sound. The column vectors of mixing matrix $\mathbf{A}$ or basis features can be used as a valid feature set to detect changes in the respiratory patterns. Two test functions are proposed to track changes in the respiratory pattern. Experiments show that these two test functions can successfully detect the place where the respiratory pattern starts to change in the tracheal sound.

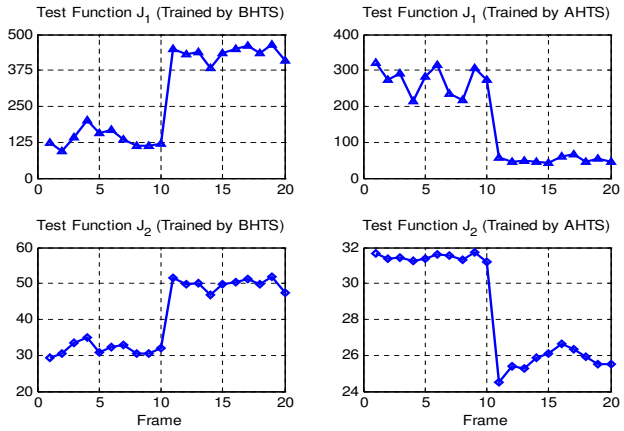

Fig. 6. Four detection results. Top left: $\mathbf{W}$ is trained by BHTS; Top right: $\mathbf{W}$ is trained by AHTS; Bottom left: $\mathbf{W}$ is trained by BHTS; Bottom right: $\mathbf{W}$ is trained by AHTS.

References

[1] M. King, D. M. Phillips, D. Wight, D. Gross and H. K. Chang, "Tracheal mucus clearance in high-frequency oscillation effect of peak flow rate bias", *Eur Respir J Suppl*, 1990. 3(1): pp. 6-13.

[2] R. P. Tomkiewicz and M. King M., "Effects of oscillation air flow on the rheological properties and clearability of mucous gel stimulants", *Biorheology*, 1994. 31(5): pp. 511-520.

[3] S. Butler, et.al. "High-frequency chest compression therapy: a case study", *Pediatr Pulmonol*, 1995. 19: pp. 56-59.

[4] L. Hansen and W. J. Warwick. "High frequency chest compression system to aid in clearance of mucus from the lung", *Biomed Instru and Tech*, vol 24, 1990, pp. 289-294.

[5] J. Lee, Y. W. Lee and W. J. Warwick. "High Frequency Chest Compression Effects Heart Rate Variability", *EMBS 2007,29th Annual International Conference of the IEEE*, 22-26 Aug.2007 page:1066-1069.

[6] J. Lee, Y. W. Lee and W. J. Warwick. "High frequency chest compression effects on cardio-respiratory interaction", *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE* , 20-25 Aug. 2008 Page(s):2447 - 2450.

[7] M. E. Davies and C. J. James, "Source separation using single channel ICA," *Signal Processing*, vol. 87, issue 8, pp.1819-1832, August, 2007.

[8] J.-H. Lee, H.-Y. Jung, Te-Won Lee and Soo-Young Lee, "Speech feature extraction using independent component analysis," *Acoustics, Speech, and Signal Processing, 2000. ICASSP '00. Proceedings. 2000 IEEE International Conference on*, pp.1631-1634 vol.3, 2000.

[9] A. Cichocki and S. Amari, *Adaptive Blind Signal and Image Processing*, Wiley, Jun. 15, 2002.

[10] J. V. Stone, *Independent Component Analysis: A Tutorial Introduction*, The MIT Press, September 1, 2004.

[11] J.-F. Cardoso, "Multidimensional independent component analysis," *Proceedings of ICASSP'98*, Seattle, WA. pp. 1941-1944.

[12] A. Hyvarinen, "Fast and robust fixed-point algorithms for independent component analysis," *Neural Networks, IEEE Transactions on* , vol.10, no.3, pp.626-634, May 1999.

[13] A. J. Bell and T. J. Sejnowski, "An Information Maximization Approach to Blind Separation and Blind Deconvolution," N*eural Comput.*, vol. 7, no. 6, pp. 1129-1159, Nov. 1995.

[14] J. F. Cardoso, "Infomax and maximum likelihood for source separation," *IEEE Letters on Signal Processing*, 4:112-114, 1997.

[15] A. Hyvarinen, "Complexity Pursuit: Separating interesting components from time-series," *Neural Computation*, 13, 2001.

[16] A. K. Fletcher; K. Ramchandran; V. K. Goyal, "Wavelet denoising by recursive cycle spinning," *Image Processing. 2002. Proceedings. 2002 International Conference on* , vol.2, pp. II-873-II-876 vol.2, 2002.