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A Study of Heart Sound and Lung Sound Separation by Independent Component Analysis Technique

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***Abstract*—In the hospital, using percussion and auscultation are the most common ways for physical examination. Recently, in order to develop tele-medicine and home care system and to assist physician getting better auscultation results; electric stethoscope and computer analysis have become an inevitable trend. However, two important physical signals heart sound and lung sound recorded from chest overlap on spectrum chart [1]. Therefore, in order to reduce human factor (ex. misplace or untrained of using) and minimize correlated effect in computer analysis; it's necessary for separated heart sound and lung sound. Independent component analysis can divide these sounds efficiency [2][3][4]. In this paper, we use two microphones to collect signals from left and right chest. We have successfully divide heart and lung sounds by Fast ICA algorithm. Therefore, it can assist physician examine and also using on Tele-medicine and Home care by this way.**

Index Terms - Heart sound, Lung sound, Auscultation, Independent Component Analysis

I. INTRODUCTION

Auscultation is a common used by physicians to examine heart functions. A senior physician often lot of experience. Besides, auscultation is more important in telemedicine and it is difficult to teach patients or users to place the stethoscope in the right position. Therefore, in telemedicine and home care system, it is necessary to divide heart sound and lung sound when sending signals to hospital's server from home. Principal Component Analysis (PCA) is often used in Pattern recognition. The PCA performed by the Karhunen-Loèkve (KL) transform produces features, that are mutually uncorrelated. The result obtained by the KL transform solution is optimal when dimensionality reduction is the goal and one wishes to minimize the approximation mean square error. However, for certain applications the obtained solution falls short of the expectations. In contrast, the more recently developed *Independent Component Analysis* (ICA) theory, e.g.,[2] [3][4][5][6], tries to achieve much more than simple decorrelation of the data. In the ICA application, signal is separated in many different domains [9]-[13].The frequency of lung sound is from 25Hz-1500Hz and that of heart sound is from 20Hz-150Hz. Thus, there is heavy for overlapping in the frequency of the heart and lung sound. Thus ICA is an applicable method for their separation.

II METHOD

A.Hardware system

As showing fig1, two microphones were used to collect the right chest sound (source 1) and the left chest sound (source 2).

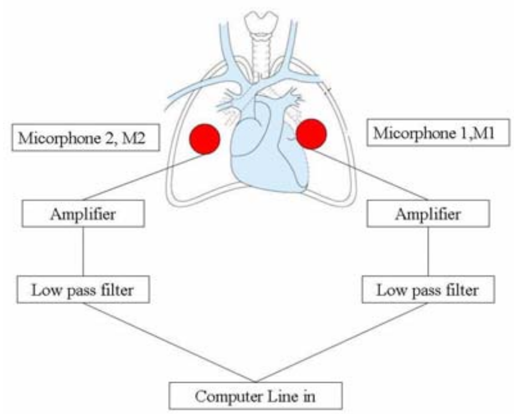


Figure 1. The Hardware System

For the electric stethoscope, two electrical condense microphones are used and amplified the collected signals 20 times. The low pass is the 3rd order Chebyshev filter and the cutoff frequency is set to 2000Hz [14]. The outputs are fed to line-in in stereo format. The line-in is connected to the computer sound card for recording and processing.

B.ICA Algorithm

The sound separation algorithm can be stated in the following equations: From the source signals s_1 and s_2, the received signals x_1 and x_2 at microphone M_1 and M_2 can be represented as

$$x_1 = a_{11} . s_1 + a_{12} . s_2 \qquad (1)$$

$$x_2 = a_{21} . s_1 + a_{22} . s_2 \qquad (2)$$

or in matrix equation:

$$x = A . s, \qquad (3)$$

We need to find the demixing matrix $\boldsymbol{W}$ so that:

$$\boldsymbol{Y} = \boldsymbol{W} . \boldsymbol{x} , \qquad (4)$$

where $\boldsymbol{Y}$ is the as close as possible to the

source signals.
The algorithm that used in this study basically consists of two steps, preprocessing and the FastICA algorithm itself. The preprocessing process consists of centering and whitening steps. The centering step is done by subtracting the mean of the observed data $\boldsymbol{x}$. Therefore, the result of this step provides zero mean data. The whitening step is used to remove the correlation between the observed data. A common method to achieve whitening is by the eigenvalue decomposition of the covariance matrix of the mixed signal. The final step is the FastICA algorithm that can be summarized as follow:

1). Center the data to achieve mean zero.
2). Whiten the data to give.
3). Choose an initial (e.g., random) vector $\boldsymbol{w}$ of unit norm.
4). Calculate
w+ = E{x.g(wT.x)} -E{g'(wT.x)}.w
5). Let ***w = w+/|w+|***
6). If not converged, go back to step 4.

The term *converge* in step 4 above refer to the condition that the value of $\boldsymbol{w}$ of the current iteration is the same as the previous $\boldsymbol{w}$ value. $\boldsymbol{E}$ denotes the expectation. The function *g(.)* should have either as:
$g_1(u) = \tanh(a_1 .u)$, where a_1 is any value that fulfills $1 \leqq a \leqq 2$ [15].

III Result and Discussion

As showed in figure 2a and 2b, the left and right chest sounds were recorded for 25 seconds that. The sample rate was 44k Hz. The major sound recorded from the right chest sound is lung sound. The major sound recorded from the left chest sound is heart sound. However, without using this system the mixed sound will be recorded from two microphones. The figure 3a and 3b is the result obtained using $g_1(u)=\tanh(a,u)$. The separation of the S1 and S2 signals can be clearly observed. The figure 4 is showed the result of the FastICA that used the function $g_2(u) = u$. $\exp(-u_2/2)$. The figure 5 is the result for function $g_3(u) = u^2$. This result can't clearly discriminate heart and lung sound. Thus, it is important to choose the function g in FastICA.

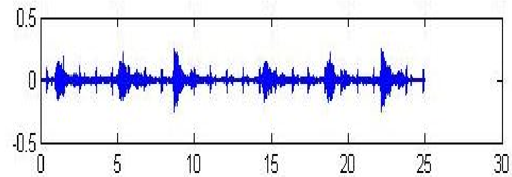


Fig. 2a right Chest Sound

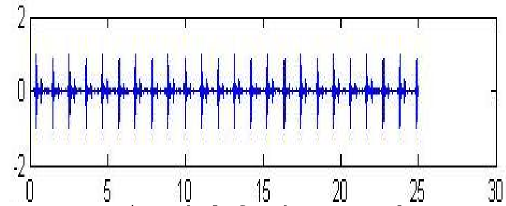


Fig. 2b left Chest Sound

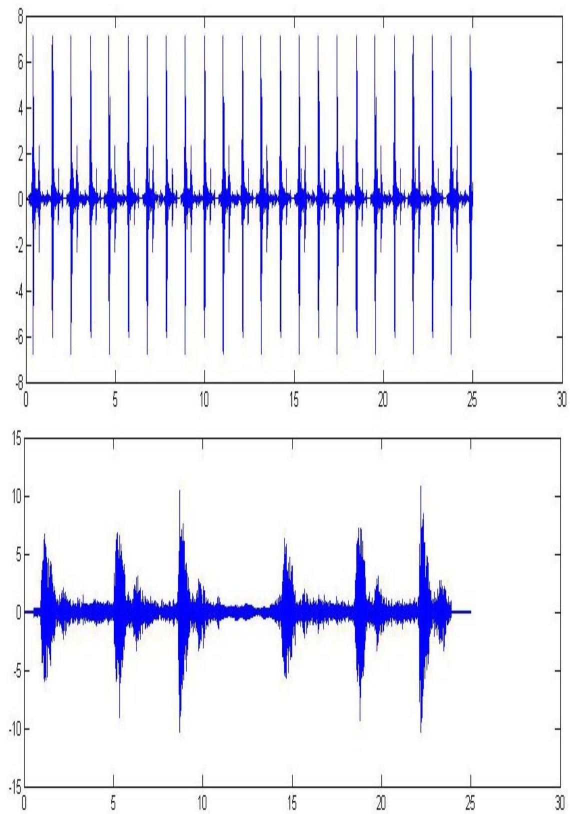


Fig. 3
(a) The Result of the FastICA Analysis by *g1(.)* (Heart Sound)
(b) The Result of the FastICA Analysis by *g1(.)* (Lung Sound)

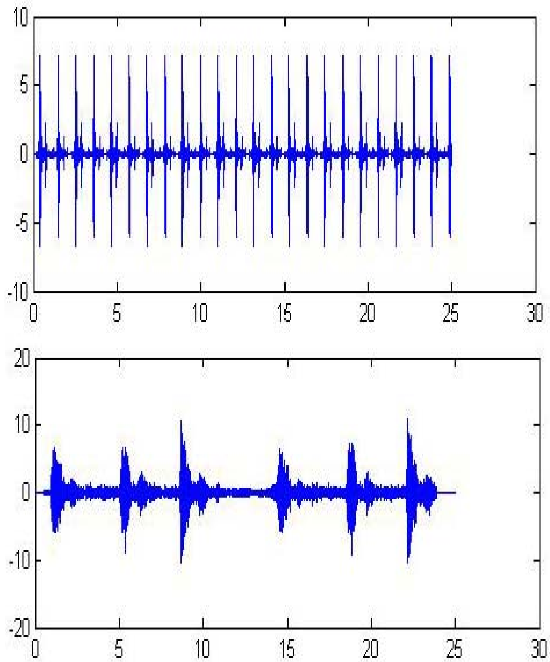


Fig. 4 The Result of the FastICA Analysis by *g2(.)*

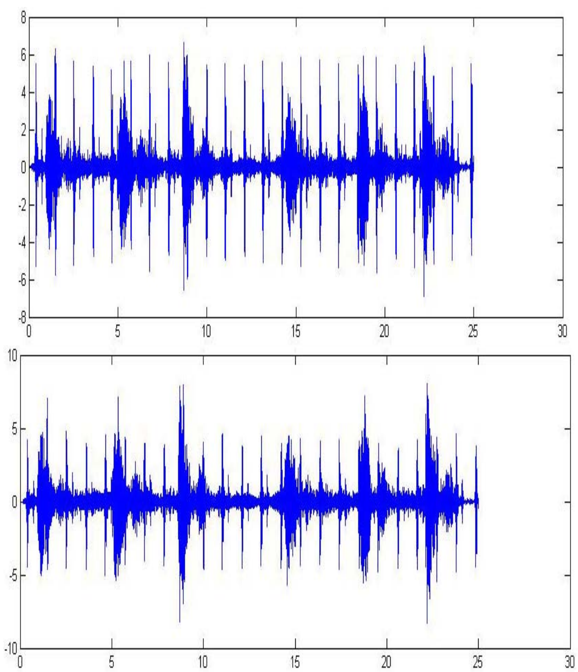


Fig. 5 The Result of the FastICA Analysis by *g3(.)*

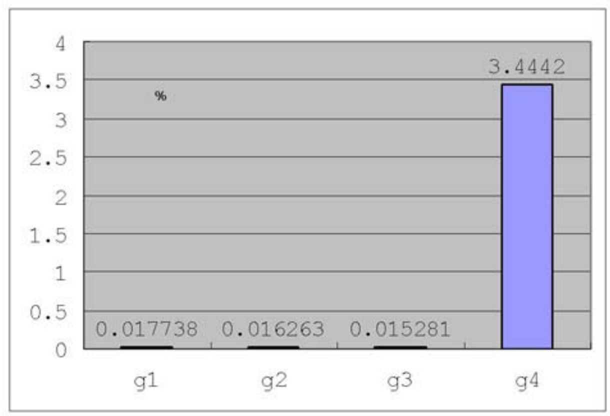
IV Conclusion

From the result, FastICA is useful tool to separate lung sound and heart sound. This is a simple effective method to separate heart and lung sound. We estimate the relative error for every g function. The error was computed as

$$\mathrm{Error} = \frac{\|O_j - S_j\|_2}{\|S_j\|_2} \bullet 100\% \qquad (5)$$

Where Oj is the original source and Sj is estimated source [16]. The figure 6 is the result of the relative error for four g functions. From the result, the performance of the method can be optimized by choosing a suitable nonlinearity function g. Therefore, one useful approach is to use generalize higher-order cumulant approximation. It uses expectations of general nonquadratic functions, or "nonpolynomialmoments" [16].

We find that saturation made the linearity relation to be destroyed between the received signals. The noise that added to the signal from the internal sources of the patient's body or acquisition process has reduced the accuracy of the results. Furthermore, there are two microphones in our system and it seems difficult to be used by the elder. However, this system must be measured by touching tightly the patient's chest. Similar application of the ICA technique can be used to separate the heartbeat of the mother and the baby in the pregnant mother. Such application can be extremely useful in monitoring the baby's cardiac function.



$g_1(y) = \tanh a_1 y$ $g_2(y) = y\exp(-y^2/2)$ $g_3(y) = y^3$ $g_4(y) = y^2$

Fig. 6 Percent relative error of separation of the artificial sparse recovered by four g functions.

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