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Analyzing the Phonocardiogram of ASD-Patient Based on Independent Component Analysis

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Abstract

About 7‰ to 11‰ of infant born with congenital heart defects (CHD) each year in China. It has made a serious mischance by CHD to our society and the families which suffered from CHD. Atrial Septal Defect (ASD) is the most incident among CHD cases. It is highly necessary to make pre-diagnosis by digital signal processing. Heart sounds provide physiological and pathological information on the structural integrity and function of the heart. The phonocardiogram (PCG) is a graphic representation of the heart sounds. Independent component analysis (ICA) is a novel method developed in recent years. In this study, the phonocardiogram (PCG) was separated into four components by applying ICA. Then interested characters were extracted based on the result of ICA. The result showed it could successfully separate the ASD-patient's PCG from normal one based on the characters.

1. Introduction

According to the statistics from web-side of PEOPLE HEALTH, it is about 7‰ to 11‰ of infant born with congenital heart defects (CHD) each year in China. The number of children with CHD is increasing in 100,000 each year. It has made a serious mischance by CHD to our society and the families which suffered from CHD. And atrial septal defect (ASD) is the most incident among CHD cases.

The septum is a wall that separates the heart's left and right sides. Septal defect is sometimes called a "hole" in the heart. A defect between the heart's two upper the atria is called an ASD. Hearing a heart murmurs during a physical exam is the first clue that an ASD may be present.

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Up till now, auscultation is still the first and basic diagnosis method to evaluate the function of the heart. However, detecting relevant symptoms and making a diagnosis based on hearing sounds is a skill that would take years to acquire and refine. So it is necessary to using technique of digital signal processing to deal with the heart sounds.

The phonocardiogram (PCG) is a graphic representation of the heart sounds. It contains valuable information of cardiac vascular system. PCG usually comprises S1 (first heart sound), S2 (second heart sound), S3 (third heart sound), S4 (fourth heart sound), and murmurs in each cardiac cycle. But an abnormal PCG such as ASD may contain pathologic murmurs and other additive sounds.

The complex and highly nonstationary of PCG signals can make them challenging to analyse in an automated way. However, recent technological developments have made extremely powerful digital signal processing technique both widely accessible and practical. Local frequency analysis and wavelet approaches are particularly applicable to problems of this type. Some of these methods have been applied to study the correlation between these sounds and various heart defects.

In this paper, a new method, independent component analysis (ICA) was used to separate PCG into four independent components. The application of ICA is pre-processing, and then interested characters were extracted based on the result of ICA.

2. Method

2.1 Principle of ICA

Imagine that there is a room where two people are speaking simultaneously. There are two microphones, which held in different locations. The microphones

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record two signals, denoted by x_1 and x_2 respectively. Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, denote by s_1 and s_2 respectively. It could express as linear equations:

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

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

Where a_{11}, a_{12}, a_{21}, and a_{22} are some parameters that depend on the distances of the microphone from the speakers.

What we need to do is estimating source data s_1 and s_2 from observation data x_1 and x_2 under the condition that s_1, s_2 and a_{ij} are unknown. This is called the cocktail-party problem [2].

Independent component analysis is originally developed to deal with problems that are closely related to the cocktail-party problem.

To rigorously define ICA, we can use a statistical "latent variables" model. It is convenient to use vector-matrix notation. Let us denote by X the random vector whose elements are $x_1,...,x_n$, and likewise by S the random vector with elements $s_1,...,s_m$. Let us denote by A the matrix with elements a_{ij} .All vectors are understand as column vector; Using this vector-matrix notation, the above mixing model is written as Eq.(3).

$$X = AS. \quad (3)$$

The statistical model in Eq. (3) is called independent component analysis, or ICA model. The ICA model is a generative Model, which means that it describes how the observed data are generated by a process of mixing the components s_i. The independent components are latent variables, meaning that they cannot be directly observed. Also the mixing matrix A is assumed to be unknown. The vector X is only can be observed. We must estimate both A and S using the ICA model.

The purpose of ICA is estimating S from X. It is possible to estimate ICA if satisfy conditions as follows [2]. (1) The components $s_1,...,s_m$ must be statistical mutually independent. (2) The independent components $s_1,...,s_m$ must be non-Gaussian distribution or just one of the components is Gaussian distribution. (3) The dimension of X must exceed or equal to the dimension of S, i.e. $n \geq m$. In this study, we assume $n = m$. PCG basically satisfies condition as mentioned above. So it makes possible to apply ICA for PCG.

2.2 Solution

ICA is an approach that based on high-order statistical characteristic of signal. It does some linear decomposition for the observed vector X, which separates X into independent components. The key of ICA is to establish an objective function which scales the independence of result and an algorithm that optimizes the objective function.

Let us now assume that the data vector X is a mixture of independent components. For simplicity, let us assume that all the independent components have identical distributions.

To see how this leads to the basic principle of ICA estimation, let us make a change for Eq. (3).

$$Y = WX = WAS. \quad (4)$$

If we can find W for the estimation of A^{-1}, that Y is an estimation of S. Thus, the solution of ICA is the estimation of the matrix W.

Intuitively speaking, the key to estimating the ICA model is non-Gaussianity. Actually, without non-Gaussianity, the estimation is not possible at all. To use non-Gaussianity in ICA estimation, we must have a quantitative measure of non-Gaussianity of a random variable. The classical measure of non-Gaussianity is kurtosis (the fourth-order cumulant) [1].

The kurtosis of y is classically defined by Eq. (5) if the mean of y is zero.

$$kurt(y) = E\{y^4\} - 3(E\{y^2\})^2 \quad (5)$$

Thus, kurtosis is zero for a Gaussian random variable. For most (but not quite all) non-Gaussian random variables, its kurtosis is non-zero [1].

Kurtosis can be either positive or negative. Random variables that have negative kurtosis are called sub-Gaussian, and those with positive kurtosis are called super-Gaussian.

Typically non-Gaussianity is measured by the absolute value of kurtosis. The square of kurtosis can also be used. Kurtosis, or rather its absolute value, has been widely used as a measure of non-Gaussianity in ICA and related fields. The main reason is its simplicity in both computational and theoretical.

Before applying an ICA algorithm, it is important to do some pre-processing for the data. It will make ICA estimation simpler and better conditioned. The most basic and necessary pre-processing is whitening. It means that before the application of ICA algorithm, we do a linear transform for the observed vector X. So we obtain a new vector Z which is white, i.e. its components are uncorrelated and their variances equal

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unity. In other words, the covariance matrix of Z is equalled to the identity matrix.

One popular method for whitening is to use the eigenvalue decomposition (EVD) of the covariance matrix as Eq. (6) [2].

$$E\{XX^T\} = EDE^T \tag{6}$$

E is the orthogonal matrix of eigenvectors of $E\{XX^T\}$ and D is the diagonal matrix of its eigenvalues. $D = diag(d_1, \cdots, d_n)$. Whitening can now be done by Eq. (7).

$$Z = ED^{-\frac{1}{2}}E^T X \tag{7}$$

Where $D^{-\frac{1}{2}}$ is computed by a simple operation as $D^{-\frac{1}{2}} = diag(d_1^{-\frac{1}{2}}, \cdots, d_n^{-\frac{1}{2}})$. It is easy to check that now $E\{ZZ^T\} = I$.

2.3 Fast Fixed-point Algorithm

For quickening the computational speed of algorithm, which takes kurtosis as objective function, Oja.E advanced Fast Fixed-point Algorithm [2]. It is a study process to get W by maximizing the kurtosis.

The basic procedure of the Fast Fixed-point ICA algorithm is as follows. It is here assumed that the data is pre-processed by whitening as discussed in the previously.

1. Choose an initial (e.g. random) weight vector w_i, and $\| w_i \| = 1$. $k = 1$.
2. Let $w_i(k) = E\{Z(w_i(k-1)^T Z)^3\} - 3w_i(k-1)$
3. Let $w_i(k) = w_i(k) / \| w_i(k) \|$.
4. If $\| w_i^T(k) w_i(k-1) \| = 1$, exit cycle, else $k = k + 1$ and go back to step 2.

Note that w_i is a column vector of W. For the separation of the observed vector X, it means find a non-Gaussian independent component $s_i = w^T{}_i Z$.

To make sure each iteration converging at the different w_i and the output $w_1^T Z, \cdots, w_n^T Z$ be decorrelated after every iteration, adding an orthogonal projection after procedure 3 as shown in Eq. (8) and (9).

$$w_i(k) = w_i(k) - ww^T w_i(k) \tag{8}$$

$$w_i(k) = w_i(k) / \| w_i(k) \| \tag{9}$$

While w is the matrix which had been estimated.

3. Analyse PCG Signals

In this study, PCG and ECG (electrocardiogram) signals were collected in the First Affiliated Hospital of Kunming Medical College. The sample frequency was 2500 Hz. The function of ECG is fixing the cardiac cycle of PCG.

One cardiac cycle of PCG signal was selected as one element of X. In clinic, PCG signal was assumed mixed by four independent components. Then at least four cardiac cycle signals should be selected as discussed in the section 2.1. In the study, four cardiac cycle signals were selected from PCG signal to establish observation vector X. For reducing the relativity of x_1, x_2, x_3, x_4, the period between two of them should be as far as possible.

After observation vector X established, it must be whitened with Eq. (7) as discussed previously. And then the whitened vector Z was analysed follow ICA procedure which was mentioned in section 2.3.

In this study, 30 cases of ASD-patient and normal PCG signals were respectively chosen. Each PCG was separated into four independent components, so there were 120 independent components for ASD-patient and normal PCG signal respectively. That there were 240 interested characters were extracted. Finally, the 240 characters were classified

4. Result and Discussion

The results of ICA were shown in the Fig.1 and Fig.2. Fig.1 showed four independent components of normal PCG; and Fig.2 showed the results of ASD-patient. The results of classifying were shown in the Fig.3. The "*" pointed the percent of murmurs in one cardiac cycle for normal PCG, and the "o" pointed the ASD-patient's one.

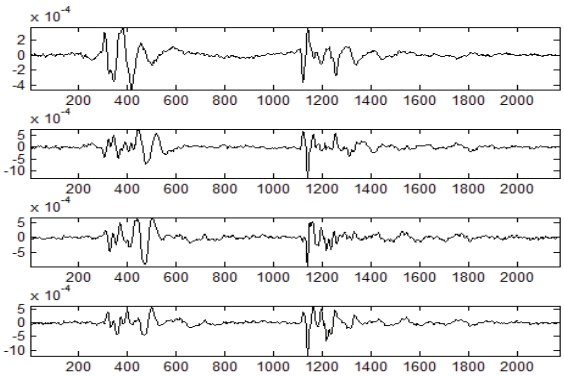

Fig.1. the result of normal PCG signal

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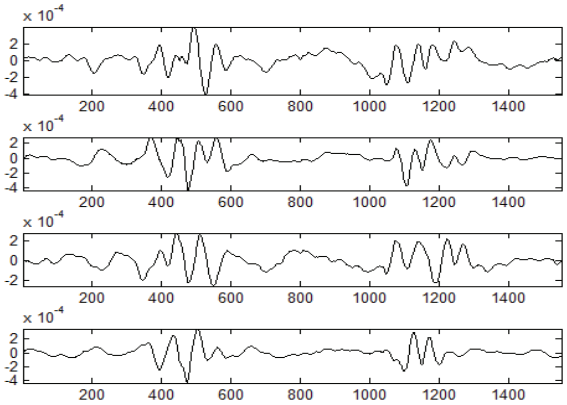

Fig.2. the result of ASD-patient's PCG signal

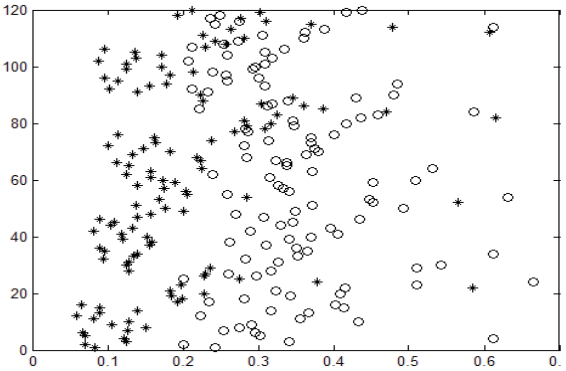

Fig.3. the result of classification

In previously text, it has been introduced that the first character of ASD-patient's PCG is hearing a heart murmurs during a physical exam. From clinic speaking, pathologic murmurs would appear between S1 and S2 in every cardiac cycle because the "hole" for ASD. So the murmurs between S1 and S2 are important character which was interested. This was the reason why the murmurs were chose as character.

PCG signal is biologic signal; it has randomicity in many aspects, such as the cycle, the intension are different for different people. If absolute value was chose as character, individuality is too obvious; it goes against to classify. But if we take the percent as character, it can accurately reflect the difference for different people. This was the reason why the percent of murmurs was chose as character.

From Fig.3, it was easy to distinguish normal PCG from ASD one; and the result of this study was accorded with the clinical diagnosis.

5. Conclusion

We have presented a fast fixed-point algorithm based on kurtosis for the separation of PCG; it could separate effectively the ASD and normal PCG. Farther analysis was done based on the result of ICA. The farther analysis was positive for the analysis of PCG signal.

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