Noninvasive Study of the Human Heart using Independent Component Analysis

Yi Zhu, Tong Lee Chen, Wanping Zhang, Tzyy-Ping Jung, Jeng-Ren Duann, and Chung-Kuan Cheng, Fellow, IEEE

Abstract — We develop a new approach to study the human heart using independent component analysis. Electrocardiogram (ECG) is an important tool for heart disease diagnosis. However, the normal 12-lead ECG can only obtain limited heart signals and mostly rely on trained and experienced medical doctors to perform the analysis. We have designed experiments so that high spatial of electronic signals can be recorded from human subjects. Independent component analysis is applied to the recorded signals to separate different components from the recorded waves. The various separated components are further analyzed by back-projecting their activities to the surface montage to examine the properties of components. Experimental results show that this is a promising approach and is able to be extended to perform more sophisticated heart simulations.

I. INTRODUCTION

A computer model that can simulate the heart is a complex topic that medical researchers have been working on for decades. Being able to model a heart provides the ability to diagnose heart diseases efficiently, allowing doctors to easily locate the problem or perhaps point out which part of heart wall might be failing. One ideal for the model is its ability to take measurements in a noninvasive manner. Not only is it more cost effective for patients, it is also much simpler and faster to prepare, setup and take measurements than the invasive counterpart in going through surgery. Although electrocardiogram (ECG) can take measurements of the heart noninvasively to record the amount of electrical force at a given point on the body, a healthy subject could have abnormal heart rhythm while a known heart diseased subject could have normal heart rhythm. Thus merely studying ECG readings is not enough in diagnosis. To get a better understanding of how the heart works would require the ability to separate out the sources of the heart and understand how each source contributes to a pulsating heart.

In this paper, we propose an approach to make use of Independent Component Analysis (ICA) techniques to analyze electronic heart signals, which are obtained by our experiments. ICA refers to a family of related algorithms that performs blind source separation when statistical independence are taken into account[1]. Although multiple channel recordings were used by other researchers, such as [2][3][4], to study human heart activities, there are not many previous works trying to separate and study the different independent components embedded in the recorded heart waves by high density electrodes. As we mentioned above, it is of importance to identify different underlying sources that generate heart waves, which is approached by ICA algorithms in this work. The experimental results show that different components of the P-wave, QRS complex and T-wave, can be clearly identified and their corresponding back projections demonstrate different properties, which is a clear sign to show that it is a more effective way to locate the underlying problems of human hearts than normal ECG.

The rest of the paper is organized as follows: in next section, the ICA concept and algorithm will be presented; Section 3 will introduce how our experiments are conducted and their results; future work will be discussed in Section 4.

II. INDEPENDENT COMPONENT ANALYSIS

Our methods are based on the theory of ICA, which was originally proposed to solve the blind source separation problem [5]. At that time, Comon was hoping that a defined mathematical framework would allow a baseline in further development of the ICA concept. The research effort in ICA was considered small scale until the mid 1990s where it gained more attraction and popularity from Bell and Sejnowski’s infomax principle [1]. Jung et al. applied the ICA technique on many different types of biomedical signals including ECG, electroencephalogram(EEG), MEG (the magnetic counterpart to EEG), and functional magnetic resonance imaging (fMRI) scans [6][7]. In the ECG study, Jung et al. took eight channels of measurements on the surface of a mother’s chest and abdomen. The channels were then processed using ICA to separate the maternal and fetal heart beats. According to their study, Jung et al. discovered that, although biomedical signals provide abundant information about the physiological process, they are often contaminated by distortions caused by small movements of the electrical contacts known as artifacts. ICA, on the other hand, shows promise in separating artifacts from source signals, and perhaps can further separate components into more fine grained subcomponents. There are also other previous works [8][9][10][11] that tried to use ICA to remove artifacts in the ECG recording. In this work, instead, we design more elaborate experiments to collect high density heart signals and use ICA to analyze underlying heart activities. We shall first introduce...
the ICA concept and algorithm, which is the core technique we use.

$N$ source signals $s = \{s_1(t), \ldots, s_N(t)\}$ can be linearly mixed by multiplying a mixing matrix $A$ and produce $N$ mixture signals $x = \{x_1(t), \ldots, x_N(t)\} = As$. When the mixture signals $x$ are known, we would like to recover a version, $u = Wx$, of the original sources, $s$, identical save for scaling and permutation, by finding a square matrix, $W$. The key assumption used in ICA to solve this problem is that the source signals are as statistically independent as possible during the time courses. Statistical independence means the joint probability density function (pdf) of the output sources can be factorized to the product of the marginal pdfs of each source:

$$p(u) = \prod_{i=1}^{N} p_i(u_i)$$

(1)

There are quite a few ICA algorithms, such as Hyvarien’s FastICA and Cardoso’s fourth-order algorithm JADE [12][13]. They have similar performance when generally compared. However, when applied to actual data sets, they may produce difference solutions and the significance are hard to measure. The review papers [14][15] compared various ICA algorithms and their interrelationships. Here we employ the gradient ascent algorithm implemented by Makeig et al. [16], which is based on the infomax ICA algorithm and has been proven to be effective in analyzing biomedical signals. In the following we briefly sketch the infomax ICA algorithm and the gradient ascent approach.

The objective of the infomax ICA algorithm is to minimize redundancy between the outputs, which is the following mutual information

$$I(u) = \int p(u)\log \frac{p(u)}{\prod_{i=1}^{N} p_i(u_i)} du$$

(2)

This redundancy measure has value 0 when the pdf $p(u)$ can be decomposed as in Equation (1), and is a difficult function to minimize directly. Therefore the infomax algorithm relates this function to the joint entropy, $H(g(u))$, where $g(u)$ is the cumulative density function (cdf):

$$I(u) = -H(g(u)) + E \left[ \log \frac{|g'(u_i)|}{p_i(u_i)} \right]$$

(3)

If the absolute values of the slopes of the cdfs, $|g'(u_i)|$ are the same as the independent component pdfs, $p_i(u_i)$ then maximizing the joint entropy of the $g(u)$ vector will be equivalent to minimizing the redundancy in the $u$ vector.

Based on this idea, the unmixing matrix $W$ can be updated iteratively using the following equation [16]:

$$\Delta W = \epsilon \frac{\partial H(g(u))}{\partial W} W^TW = \epsilon (I + \hat{y}u^T)W$$

(4)

where $\epsilon$ is the learning rate and vector $\hat{y}$ has the elements $\hat{y}_i = (\partial / \partial u_i) \log(\partial g_i(u_i)/\partial u_i)$. The $(W^TW)$ “natural gradient” term in the update equation avoids matrix inversions and speeds convergence by normalizing the variance in all directions [16]. Thus, $W$ is first initialized to the identity matrix $I$ and iteratively updated using the above equation until the change of the matrix is less than a certain threshold.

## III. Experiments

### A. Equipments & Setup

Our experiments are based on BioSemi’s ActiveTwo Base system (http://www.biosemi.com/). A list of the main necessary equipments is as follows:

- 16 × 8-channel amplifier/converter modules
- 4 × 32 pin-type electrodes
- Packer Signa electrode gel
- 128 electrode holders
- CMS/DRL electrodes
- LabView software
- adhesive pads

The system consists of 128 pin-type electrodes that are designed for use with BioSemi’s headcap using the electrode holders (At most 101 of them are used in our experiments). The electrode holders are attached to the skin of the chest and back of the subject by adhesive pads, each by each. The Ag/AgCl electrodes do not require skin preparation, but does require electrode gel to act as a conductor between the skin and the electrodes themselves. The electrodes are connected to a 256 channel AD-box that is powered by the battery box. The AD-box is the multi-channel mapping system and requires one amplifier/converter module per 8 channels in use by the AD-box. The AD-box then feeds data measurements through the USB2 receiver that is connected to a computer. The computer can then save the data via the LabView software for further analysis. We set the sampling rate to be 256 points per second.

### B. Procedures

The preliminary experiments are performed on two subjects. For each subject, the preparation procedure consists of the following steps:

1. Attach electrode holders to the skin of the subject by adhesive pads. They are attached to the chest and back of the subject respectively, forming two identical size matrices. In our two experiments, we chose the sizes of $6 \times 6$ and $7 \times 7$ respectively.
2. Inject adequate amount of Parker Signa electrode gel in the electrode holders using a syringe and blunt needle.
3. Plug in electrodes to the holders.
4. Place three electrodes on the subject’s left arm, right arm and left leg as the unipolar limb leads to form the Wilson Central Terminal and place the electrodes CMS/DRL on the subject’s waist as the grounding electrodes.
5. Connect electrodes to the AD-box and set up the rest of BioSemi’s hardware.

When the subject is ready for measurement taking, he is in a relaxed standing position. Although a supine position is ideal in ECG recording, it is not desirable in this case because there is a substantial risk to damaging the
electrodes that are placed on the back of the subject. The subject is asked to do the following four kinds of activities:

1. Standing still and breathing normally for 90 seconds. It is used as a baseline for comparison to the rest of the activities.
2. Breathing and holding the breath for intervals of 10 seconds alternatively for a period of 90 seconds starting with the breathing interval. It is used to tire out the cardiac muscles so that the contractions of the various muscles will start to separate as shown in the wave forms.
3. Horse stance for a certain period for 60 seconds and record the waveforms after that. Its function is similar to the above but in a more extreme measure.
4. Leaning to different orientations. The first subject is asked to lean forward and left and the second subject is asked to lean in four orientations (forward, backward, left and right). In each orientation 90-second waveforms will be recorded.

In the analysis, we only take the last 50 seconds recording of each activity, because the early phase of activities may contain more noise. We use multiple activities in order to make the heart show different results under different conditions. ICA can then pick up the subtle differences and decompose the waveforms into true source components.

C. Results & Analysis

As we mentioned above, we performed the experiments on two subjects, with 72 electrodes (two $6 \times 6$ matrices on the chest and the back) and 98 electrodes (two $7 \times 7$ matrices on the chest and the back) respectively. The 72 electrodes (also called channels) are numbered as shown in Figure 1 — note that the left and right orientation in the chest and back are reverse since they can form a circle around the body; in the $7 \times 7$ case they are arranged in the similar fashion. Figure 2 are the photos taken for the second subject. For the first subject, we recorded 5 activities: still standing, holding breath, horse stance, leaning forward and left; for the second subject, we recorded 7 activities, with the additional leaning backward and right activities. The recorded raw data is first processed by two-way least-square FIR (Finite Impulse Response) filtering, with the low-edge frequency in pass band 0.1 Hz and the high-edge frequency in pass band 40 Hz. Figure 3 and Figure 4 show the partial recorded raw mixture signals respectively. The left portions of the two figures show the wave forms of the still standing phase, and the right portions show the wave forms after horse stance. It is observed that the electrodes on the chest receive much stronger signals than the ones on the back. It is reasonable since the human heart is closer to the front of the body. Regarding the waveforms of the two subjects, they have different characteristics. For instance, the first subject seems to have stronger T-waves and the second one contains P-waves. For each subject, compare the waveforms recorded in different activities, we find that they appear to have different characteristics as well, such as the rate of the beat and also the shape of the QRS and T-waves.

The ICA algorithm is applied to the above two waveforms. By the definition, $W$ is a square matrix, therefore there are 72 and 98 components are produced respectively. However, only a few of them has relatively large amplitude and have meaningful waveforms. We believe the rest of them are generated by breath and noise thus filter them out. Figure 5 and Figure 6 show the meaningful components produced by the ICA algorithm for the two subjects respectively.

From the results, we have the following observations:

- The ICA algorithm is able to separate P-wave, QRS complex and T-wave. In two experiments, T-wave can be clearly separated. Also, P-wave is successfully separated in the second subject.
- Multiple activities are essential to perform ICA successfully. We have tried different combinations of the waveforms by each activities. The experimental results show that at least three activities are needed to decompose the T-waves. And more activities guarantee better separation. This is because different sources would have different behaviors under various circumstances; for example, the shape of the T-waves and its distance to the QRS complex are different in different activities, as shown in Figure 3 and Figure 4.
- The ICA algorithm can detect around 7-8 different components from the original waveforms. Especially, there are multiple components which belong to the QRS components. This phenomenon indicates that the QRS complex wave may be generated by various underlying sources. For subject 2, even the T-wave is decomposed to two components, which shows that even T-wave is probably not a simple activity.
- Note that the components that form the QRS complex have different peak time (they have been sorted in the ascending order of peak time). They could represent a sequence of wave propagation. Thus, it is useful to further analyze these components and detect the physical positions of the sources that produce these components. We will present the analysis in the following.

To further analyze the components, we use the back projection technique to plot the location maps for each component. From the ICA algorithm, we obtain the unmixing matrix, $W$, then the mixing matrix will be $W^{-1}$. Thus we have $x = W^{-1}u$. Let $W^{-1}(:,:,i)$ denote the $i$th column of $W^{-1}$, and $u(i,:)$ denote the $i$th row of $u$, then back projection for component $i$, $p_i$ can be computed as

$$
p_i = W^{-1}(i,i) \times u(i,:)
$$

In fact, the column vector $W^{-1}(i,i)$ represents the weight of each channel that contributes to the $i$th decomposed component. Since we have known the physical location of each channel, it's possible to plot the "potential maps" for each component according to the corresponding vector. The maps for subject 1 and subject 2 are shown in Figure 7 and Figure 8 respectively. The blue color denotes lower weights and the red color denotes higher weights.
In most of the maps, the weights are concentrated in the right part of the front chest. This is understandable since it is the closest to the human heart. Furthermore, the most concentrated part, which is highly possible to be the source place that produce these components, is different for different components. Generally, the P-wave (the first map of the second subject) source occupies the upper portion of the maps. The positions of different QRS components are moving downward with the peak waves moving in the time course. And the T-wave sources are located in the lower portion of the maps. This is consistent with the definitions of these waves: P-wave is initiated by the SA node, QRS complex represents the depolization of the ventricle, and T-wave indicates the repolization of the ventricle. Since the depolization needs to spread from the AV node to all parts of the ventricles, the sources are moving downward as reflected in the maps of different components of the QRS complex. Further computation could be done to compute the propagation speed of the waves and therefore help doctors decide whether the heart is healthy.

In addition, we also try to estimate the direction of dipoles according to the maps, by assuming that the vectors are pointing from the most negative location to the most positive location. We illustrate four of the vectors in the maps (a), (b), (d) and (f) of subject 2, which represents the components of the P-wave, early portion of the QRS complex, late portion of the QRS complex, and early portion of the T-wave respectively. The vector directions are drawn by white arrow lines, as shown in Figure 8. They have very different directions: the vector direction of the P-wave (Component 1) is pointing from the bottom right of the chest to the top left of the chest; that of the early QRS component (Component 2) is almost parallel to the ground, from the back to the chest (remember the map is an extended version); that of the late component (Component 4) is pointing from the bottom left to the center of the chest; and that of the T-wave (Component 6) is pointing from the top right of the back to the center of the chest. However, this estimation is very rough and source localization techniques should be used to calculate the origins, direction and magnitude of these vectors later.

We are calculating the wave propagation speed according to the QRS components and trying to verify whether it is consistent with the physiological observations. If this could be done, it would be helpful for doctors to detect heart diseases.

We are also seeking for a better ICA algorithm that will take the features of ECG waveforms into account. The current assumption is that all the components are totally independent. However, the sources are located in one human heart and therefore they are somehow related during the time course. We are targeting for design a new separation algorithm that can take this property into consideration and obtain more accurate component waveforms to perform the analysis.

### IV. Discussion & Future Work

The successful ICA application to electroencephalographic (EEG) signals inspired us to design experiments to collect heart signals from multiple channels and analyze them by ICA. However, it is not easy to keep the tight contact between skins and electrode holders, especially when the subjects are being asked to do various activities. The current experiment setup is able to achieve this goal but it takes time to attach the holders. We are still seeking for a better way to quickly set up the experiments with reliable attachments of holders.

It is an ongoing research project and only our preliminary experimental results are presented here. Currently we are carrying on this project in the following several directions:

- We are taking more subjects to perform the experiments in order to discover the stability of the ICA algorithm. Also, we are going to use Computed Tomography (CT) or Magnetic Resonance Imaging (MRI) to detect the physical location of each subject’s heart so that the sources of components can be more accurately located.
- We are calculating the wave propagation speed according to the QRS components and trying to verify whether it is consistent with the physiological observations. If this could be done, it would be helpful for doctors to detect heart diseases.
- We are also seeking for a better ICA algorithm that will take the features of ECG waveforms into account. The current assumption is that all the components are totally independent. However, the sources are located in one human heart and therefore they are somehow related during the time course. We are targeting for design a new separation algorithm that can take this property into consideration and obtain more accurate component waveforms to perform the analysis.

### REFERENCES


Fig. 2. Photos of Electrodes

Fig. 3. Subject 1 Mixture Waveforms

Fig. 4. Subject 2 Mixture Waveforms


Fig. 5. Source Components for Subject 1

Fig. 6. Source Components for Subject 2
Fig. 7. Subject 1 Back Projection Maps
Fig. 8. Subject 2 Back Projection Maps