

CAPTURING ECG SIGNALS BY ICA

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I. INTRODUCTION

Study of electrocardiogram (ECG) signals plays a very vital role to diagnose the malfunctioning of the heart. Electrocardiogram (ECG) machine permits deduction of many electrical and mechanical defects of the heart, by measuring potentials on the body surface. The ECG can record non invasive measurements of heart activity, due to the confounds, created by mixing of volume-conducted signals at the body surface electrodes, however, a healthy subject could have abnormal heart rhythm and a known cardiac-impaired instead of a normal heart rhythm. Thus, diagnoses, based on visual observations of recorded ECG signals, may not be accurate. So keeping this, we will use and compare the various methods and techniques to analyze electronic heart signals. One such method is ICA which refers to a family of related algorithms that performs blind source separation, separating the recorded signals into component signals that are maximally statistically independent in some sense. In this research work, we propose an approach to make use of independent component analysis (ICA) techniques to analyze electronic heart signals recorded using high-density montages. Although ICA and principal component analysis (PCA), being linear decomposition technique, have been applied to analyze atrial activities in ECG. In these studies only conventional 12-lead ECG data were used, and therefore, the number of cardiac sources that could be separated was limited to 12. Recordings with more channels have been used by other researchers, but they did not test the application of ICA to their data. Here, 98-channel ECG is recorded to facilitate use of ICA-based spatial filter to separate different heart activities. A gradient ascent ICA algorithm is adopted to separate the P-wave, QRS complex, and T-wave. The separated components are further back-projected to body surface potential maps. The experiments are conducted on five subjects to show the effectiveness of our approach. Results from five subjects show that P-, QRS-, and T-waves can be clearly separated from the recordings, confirming that ICA might be an effective and useful tool for high-density ECG analysis, interpretation and diagnosis.

The rest of the work is divided as given below :

Section II – Analysis Methods
Section III- Methodology
Section IV- Results and Analysis
Section V- Conclusions & Future work

II. ANALYSIS METHODS

Basically our works depend on the theory of ICA, which was adopted to solve the problem of blind source separation [1]. Comon proposed the mathematical framework for Independent Component Analysis (ICA). Previously ECG applications focused mainly on two directions :- De Lathauwer first applied ICA to separate fetal ECG from maternal body surface ECG recordings [2][3], successfully addressing a longstanding problem. ICA was used to remove the artifacts from ECG recordings [4]-[6] and also used to remove artifacts from both animal [7] and human [8]. But it also to be noted that they only made use of the conventional 12-lead ECG signal from which only ten channels of recorded data were available for analysis, also, did not instruct subjects to perform multiple activities. ICA separated components accounting for the QRS complex from those accounting for the P-wave and T-wave. However they were unable to further separate P-wave from T-wave. Due to this, more reliable methods are designed to collect high-density ECG signals and used ICA to separate the underlying heart activities. ICA concept and algorithm are as given hereunder:

N source signals $s = \{s_1(t), \dots, s_n(t)\}$, linearly mixed by multiplying a mixing matrix A, produce N mixture signals $x = \{x_1(t), \dots, x_n(t)\} = As$. Given the signal mixtures x, we would like to recover a version $u = Wx$. The key assumptions used in ICA to solve this problem is that the source signals are as statistically independent as possible during the time course of the recordings. 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 :

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

In practice, however, some approximation to independence or to related quantities must be used for finite data lengths. In our work, we employed the gradient ascent algorithm as implemented by Makeig [9] based on the infomax algorithm, which has been found to be effective for analysis of biomedical signals.

To evaluate the resulting independent components, back-projection is used to plot body

surface projection maps for each component. From the ICA algorithm, we obtained unmixing matrix W . The signal mixing matrix will be W^{-1} , i.e., $x = W^{-1}u$. Let $W^{-1}(:,i)$ denote i th column of W^{-1} , and $u(i,:)$ denote the i th row of u , then the back-projection of component i, p_i is

$$p_i = W^{-1}(:,i)u(i,:). \quad (2)$$

The column vector $W^{-1}(:,i)$ represents the relative (signed) weight of the i th component in each body surface channel. The back-projection map of each component may be plotted for each subject. The computation of back-projection maps is strongly reminiscent of more general body surface potential mapping (BSPM) techniques, as is the use of high density electrodes. In BSPM, 32 to 256 ECG electrodes are used to record the body surface potential field created by the beating heart. The BSPM system has been used in several hundreds of patient recording representing most common cardiac diseases such as is chemic heart disease and ventricular and supraventricular arrhythmias [30]–[32]. The main advantage of BSPM, compared to 12-lead ECG, is the ability to visualize the cardiac potential distribution across the whole thorax. Several methods have been proposed for detecting the vulnerability to life-threatening arrhythmias from BSPM recordings and from near-equivalent magnetocardiographic signals [30], [31]. In such methods, the signals from each channel are analyzed by signal processing methods such as beat-locked averaging, late potential analysis, spectral turbulence analysis, QRST integral analysis, and spatial parameter mapping. High-density ECG recording makes more signals available for analysis, necessitating automated signal processing methods, and making the method more robust to individual channel noise or dropouts. However, different from previous methods, we visualize the back-projection of each individual ECG source to the body surface, obtained by ICA decomposition, instead of visualizing the sum of these sources, i.e., the whole recorded body surface signals. The back-projected component maps may reflect properties of each ECG signal component, providing us with more information about different heart activities compared to BSPM visualizations of the whole signal mixtures.

III. EXPERIMENTS

A. Equipments and Setup

Our experiments use BioSemi's Active Two base system. A list of the main necessary equipment is as follows :

1. 16 x 8-channel amplifier/converter modules;
2. 4 x 32 pin-type electrodes;
3. Packer Signa electrode gel;
4. 128 electrode holders;
5. Common mode sense (CMS)/driven right leg(DRL) electrodes;

6. LabView software;
7. adhesive pads;

The Biosemi system incorporated 128 pin-type electrodes designed for EEG recordings with latex head caps dotted with plastic electrode holders. At most, 101 of these were used in our experiments. The electrode holders were attached to the skin of the chest and back of the subject by adhesive pads. The active Ag/AgCl electrodes do not require skin preparation, but do require electrode gel to act as a conductor between the skin and the electrodes. The signals recorded at the electrodes are synchronously converted to 24-bit digital format at 256 Hz per channel, and are saved in a computer.

B. Procedures

The experiments were performed on five electrocardiographically normal volunteer subjects as approved by an Institutional Review Board. We started each experiment by attaching 36–49 electrode wells to the chest and an equal number to the back of the subject. Then, after an adequate amount of electrode gel was injected into each well, the electrodes were plugged in. Three additional electrodes were placed on the subject's left arm, right arm, and left leg as unipolar limb leads to form the Wilson central terminal, and a grounding node electrode was placed on the subject's waist before the electrodes are connected to the recording system. A DRL circuit is used in order to minimize the artifacts. The DRL circuit is able to read what it believes to be noise (usually common mode noise) and feeds a very small amount of electricity back into the body to actively negate this noise. This technique is highly effective and has been used in medical recording devices such as ECG and EEG. Subjects were recorded in a relaxed standing position. Although a supine position is ideal in ECG recording, it was not used in this case because of the risk of damage to the electrodes placed on the back of the subject. Subjects were asked to do the following four kinds of activities:

- 1) Stand still and breathe normally for 90 s. This was used as a baseline for comparison to signals recording, during the other activities.
- 2) Breathe in and hold the breath for intervals of 10 s during a period of 90 s. This was used to tire the cardiac muscles so that the contractions of the various muscles would begin to separate as shown in the wave forms.
- 3) Maintain a horse stance for 60 s, followed by ECG recording. This exercise was used to tire subjects so that their heart would beat faster and the differing cardiac muscles contractions would allow better ICA separations.
- 4) Lean toward different orientations. One subject was asked to lean forward and to the left, and the other four subjects were asked to lean to all four cardinal orientations (forward, backward, left, and right). Ninety-

second recordings were made during each orientation.

Only the last 50 s recording of each ECG recording is analyzed, to avoid the higher noise levels in the early phase of the recordings. We used multiple activity conditions to make the heart perform slightly differently based on the concept that ICA could then pick up the subtle differences in activity patterns, and thereby better decompose the recorded signals into different components accounting for P-waves, QRS complex, and T-waves.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

We performed six experiments on five subjects, with 72 electrodes (two 6×6 matrices on the chest and the back) and 98 electrodes (two 7×7 matrices on the chest and the back), respectively. Two experiments on subject 1 were performed to verify the stability of our results. the 98 electrodes (or channels) are numbered as shown in Fig. 1—note that the left and right orientations on the chest and back are reversed so they can form a circle around the body.

		Chest						Back						
		Subject right			Subject left			Subject left			Subject right			
up ↓ down	1	8	15	22	29	36	43	50	57	64	71	78	85	92
	2	9	16	23	30	37	44	51	58	65	72	79	86	93
	3	10	17	24	31	38	45	52	59	66	73	80	87	94
	4	11	18	25	32	39	46	53	60	67	74	81	88	95
	5	12	19	26	33	40	47	54	61	68	75	82	89	96
	6	13	20	27	34	41	48	55	62	69	76	83	90	97
	7	14	21	28	35	42	49	56	63	70	77	84	91	98

Fig.1 LAYOUTS OF ELECTRODES

In the 6×6 case, they are arranged in a similar fashion. For the first subject, five activities are recorded: still standing, holding breath, horse stance, and leaning forward and left; for the other four subjects, seven activities are recorded, including the additional leaning backward and rightward poses. The recorded raw data were first processed by two-way least square finite impulse response (FIR) filtering, with the low-edge frequency in pass band 0.1 Hz and the high-edge

frequency in pass band 40 Hz. Fig. 2 shows some recorded raw mixture signals from subject 1. The left portions of the two figures show the wave forms during standing still, and the right portions the wave forms following the horse stance. Notice that the electrodes on the chest receive much stronger signals than those on the back. This is reasonable since the human heart is closer to the front of the body.

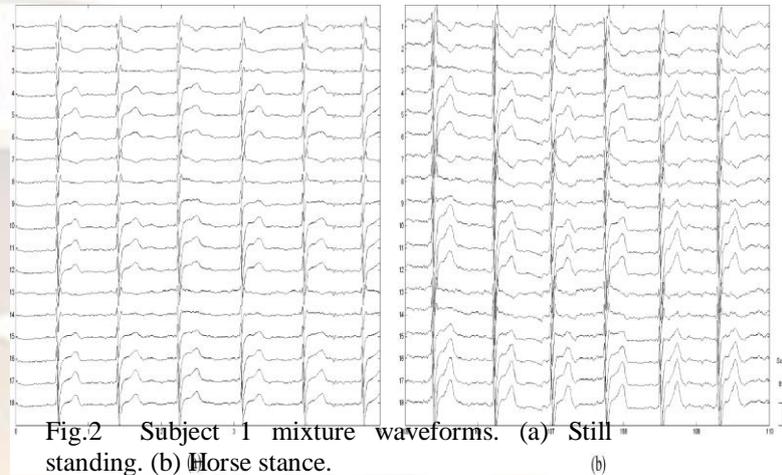


Fig.2 Subject 1 mixture waveforms. (a) Still standing. (b) Horse stance.

A-Separated Components

The ICA algorithm was then applied to the recorded signals concatenated across all recordings for each subject. By definition, W is a square matrix; therefore, 72 and 98 components were produced, respectively. However, for each subject, only a few of them had relatively large amplitudes and meaningful waveforms. We believe that the rest account for breath related and other noise, and thus, ignored them in further analysis. From the results, we made the following observations:

1) The ICA algorithm was able to identify and separate the overlapping spatial projections of the P-wave, QRS complex, and T-wave. In the experiments for all subjects, the T-wave is clearly separated from the QRS complex. P-waves are identified in three out of five subjects—through observing the original recorded signals, we confirmed that in the two cases where P-waves are not separated, the P-waves have very small magnitude and thus are buried in noise. We believe this is reasonable because QRS complex, which reflects the depolarization of the ventricles, is a complicated process that may consist of multiple heart activities. The separation results confirmed that high-quality solutions can be obtained using a dense channel array. Only the conventional 12-lead ECG signals were used in [5]. In their experiments, P-waves and T-waves could not be separated, and the separation of T-waves from QRS-complex is not as clear as ours. This suggests that high-density channels are beneficial in separation. We tried

reducing the number of channels in our experiments in [33]. We showed that using 12 or 24 channels, the ICA algorithm is still able to separate different components, though the quality is compromised. Also, the positions of these 12 or 24 channels should be carefully chosen to obtain good results. This requires further investigation.

2) Recordings during or following a variety of activities are highly useful for successful ICA source separation. Decomposing different combinations of recordings associated with different activities showed that recordings during or following at least three activities were needed to separate the T-waves, and that decomposing more recordings produced better separation. We believe this is because different sources exhibit different behaviors under various circumstances. For example, the shape of the T-waves and their latency relative to the QRS complex were different for different activities. In addition, since ICA must learn the relatively large unmixing matrix, more data are required to decompose more channels. For example, to separate 100 channels, ICA must learn 100×100 unmixing weights, typically requiring some multiple of this many data points (e.g., some multiple of 40 s using 256 Hz sampling). For successful decomposition of 100 or more EEG channels, the scaling factor may be 30 or more. An equivalent requirement, for our recordings, would call for using 11–20 min or more of data. Here, our best results were obtained by concatenating all the recordings for the subject (in all, 4–6 min of data). It is true that concatenating multichannel ECG data acquired with different conditions can potentially introduce more components. However, such a variety is good to create differences in the composition of QRS complex or other ECG feature waveforms. For example, the interval between Q and S waves may be changed in different recording conditions. Thus, when ICA sees the variability of the Q-S interval, it may separate these two important features into two or more different components. However, if we only decompose channel ECG data with single condition, wherein the Q-S interval is pretty much fixed, then we would not be able to separate the S-wave from the Q. As a result, this helps us to more consistently decompose the ECG recordings into more independent components. To be able to see more independent components is exactly the purpose here. Accordingly, to be able to acquire more ECG channels would also be essential to increase the possibility to cover the components we potentially increased by concatenating ECG channel data recorded in different conditions.

3) Typically, ICA separated seven to eight different meaningful components from the original waveforms. Multiple components accounted for the QRS components, indicating that the QRS complex is generated by a collection of underlying sources or by a moving wave of activity. For subject 2, the T-

wave was also decomposed to two components, suggesting that the T-wave probably does not have a spatially fixed source.

4) Note that the components accounting for the QRS complex have different peak latencies (in the figure, they have been sorted in ascending order). This could represent a wave propagation sequence.

Thus, further analysis of these components should prove useful, particularly modeling of the physical positions of the sources that produce these components. To show that our experimental results could be stably reproduced, we conducted the same experiments on subject 1 once more. The same analysis was performed on the obtained data. Very similar components were obtained from both experiments. To evaluate this similarity, we calculated the peak time difference of the related components from both experiments, with respect to the peak time of the first component. The results are shown in Table I.

TABLE 1
PEAK TIME DIFFERENCE FOR TWO EXPERIMENTSON SUBJECT 1

Component	1	2	3	4	5	6	7
Experiment 1	0 ms	11.2 ms	23.2 ms	39.0 ms	45.5 ms	59.4 ms	252.4 ms
Experiment 2	0 ms	15.8 ms	28.8 ms	41.3 ms	45.7 ms	63.1 ms	257.9 ms

The peak latency difference among components in the two experiments, reflecting the propagation speed of the cardiac waves, are very close except for the second and third components. Thus, our results were reproducible. The discrepancy on the second and third components may be due to the different body conditions or due to numerical errors, which need to be further investigated.

B. Back Projection

The back-projections of different components are computed according to (2) and compared with the original channel waveforms. The purpose is to show that the separated components account for different sections of the cardiac cycle. We find that each component accounts for different parts of QRS complex, confirming that ICA separates sources of different sections of the cardiac cycle. As an example, the back-projection maps for each meaningful component of subject 2 are plotted. In the leftmost column, the column vectors $W^{-1}(:, i)$, which represent (signed) weight of the i th component in each body surface channel, are plotted. For each vector, the 98 elements are organized, reflecting their physical locations in the chest and back of the subjects. The differing weights, proportional to different potential values in

the body surface, are mapped to different colors, where red represents the largest magnitude and blue represent the smallest one. When plotting, we use finer grid rather than the original two 7×7 matrices and interpolate the values in order to obtain smooth maps. For each component, we also show the 3-D maps, together with the estimated dipole vectors that point from the most negative potential position to the most positive potential position. The left 3-D map is shown from the front view and the right one from a side view. The most right column shows the time course of the most relevant independent component. In most of the maps, the weights are concentrated in the right frontal chest, as expected. Furthermore, portion of the chest and back receiving the most concentrated signal is different for different components. The maximal projection of the different QRS components moves downward and the ensuing T-wave projection maximum is still lower. This is consistent with the physiological understanding of the origins of these features. The QRS complex represents the depolarization of the ventricle, while the T wave indicates the repolarization of the ventricle. Since the depolarization needs to spread from the atrioventricular (AV) node to all parts of the ventricles, the electrical sources effectively moves downward, as reflected in the body surface projection maps for the different components accounting for the QRS complex.

V. DISCUSSION AND FUTURE WORK

Here, we report a novel experimental approach to collecting stable, high-density ECG signals and application of ICA to separate spatially fixed and temporally independent source activities from the recorded signals. The major contributions of this research are as follows.

- 1) We design experiments to record high-density (98 channels) ECG from the body surface. The recorded signals have high quality and are stable when subjects do various activities. Moreover, multi-channel recording is necessary to use ICA to separate underlying components.
- 2) We employ a gradient ascent ICA algorithm to separate signal components from the recorded body surface mixtures. For all five subjects, we are able to separate the somewhat different but highly overlapping projections to the body surface of the P-wave, QRS complex, and T-wave, and to recover the continuous signals projecting from their cardiac generators, demonstrating that our method is effective for identifying individual sources of ECG signals.
- 3) Our approach appears promising for distinguishing between different underlying cardiac conditions, compared to traditional ECG analysis.

Although results of applying ICA to high-density ECG show great promise, the analysis

method is still in its infancy. Fruitful directions for further research include the following:

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- 3) Our approach appears promising for distinguishing between different underlying cardiac conditions, compared to traditional ECG analysis. Although results of applying ICA to high-density ECG show great promise, the analysis method is still in its infancy. Fruitful directions for further research include the following.

- 1) Determining the best placements for the electrodes. One possibility is to place more electrodes on the chest closer to the heart and fewer on other body locations. However, non uniform placement should be based on more knowledge and understanding of heart physiology.

- 2) The relationship between the number of electrodes, the length of the recording, and the performance of source separation (and subsequent source localization) should be studied systematically. In preliminary experiments, we attempted to reduce the number of electrodes, but found the results to be inferior [33]. We plan to perform a more comprehensive study to assess the performance of ICA as a function of the number of sensors since in actual clinical applications, it is preferable to reduce the number of channels if possible, as this would reduce both the time required and the cost of the supplies and equipment.

- 3) It is of importance to discover to what extent different cardiac sources can be decomposed using recordings during or following different activities. Currently, we use seven conditions in our experiments; from these, components accounting for the P-wave, QRS complex, and T-wave could be separated. It should be interesting to determine whether these components are "atomic," i.e., whether each of them is generated by a single cardiac source, and consequently, cannot be further decomposed. Possible ways of testing this conjecture include adding additional activities to the experiments, acquiring more data, or comparing results of different algorithms for decomposing the mixed body surface signals.

4) Finally, sources obtained from body surface recordings by ICA might be verified more directly using intra-cardiac recordings. For this, we will need to collaborate with electro-physiologists to analyze simultaneous high-density surface ECG and intra-cardiac recordings from patients, to verify the source activities obtained by ICA. However, note that direct recordings from the heart surface should differ depending on the size of the electrode and location, and the size of the reference electrode. Thus, even in this case, performing a “ground truth” comparison may not prove straightforward. If our approach could be validated by this rigorous process, it would likely be quickly accepted into practical clinical diagnosis, since the procedure is noninvasive, the analysis may be automated, and the results can be well visualized.

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