Detecting electrocardiogram abnormalities with independent component analysis

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ABSTRACT

In this work, we apply independent component analysis (ICA) to electrocardiographic (ECG) signals for improved detection of abnormal conditions in the heart. Unsupervised ICA neural networks can demix the components of measured ECG signals. Such components may correspond to individual heart functions, either normal or abnormal. ICA neural networks have the potential to make abnormal components more apparent, even when they are masked by normal components in the original measured signals. This is particularly important for diagnosis well in advance of the actual onset of heart attack, in which abnormalities in the original measured ECG signals may be difficult to detect. This is the first known work that applies ICA to EGC signals beyond noise extraction, to the detection of abnormal heart function.

Keywords*:* Independent component analysis, blind source separation, unsupervised learning, electrocardiogram.

1. INTRODUCTION

The electrocardiogram (ECG) is an important tool in determining the state of a patient's health. In fact, it is often one of the first things a medical doctor may check in trying to understand the physical condition of a patient. Physicians undergo extensive training in interpreting ECG signals in terms of heart functions, for diagnosing heart illnesses. Such interpretations can be particularly difficult in detecting early signs of heart illness, when ECG abnormalities may not be readily apparent, even up to the actual onset of heart attack.

Signals originating in various regions of the heart are mixed in the patient's body, and these mixed signals are available as ECG recordings. Artificial neural networks with "information-in/garbage-out" unsupervised learning can blindly separate the mixed source signals. These neural networks perform independent component analysis (ICA), finding signal components that are maximally independent. In the case of ECG signals, measured signals are generally a concatenation of individual source waveforms closely separated in time. This is much like the case of phoneme de-hyphenation in speech processing, to which ICA has been successfully applied [1][2].

Such methods of intelligent signal processing have the potential to greatly enhance the analysis of ECG signals. Indeed, there have already been a number of ICA-based approaches proposed for the processing of medical signals [3][8][11][12][13][14]. For ECG signals, these have primarily focused on the removal of artifacts such as electrical mains interference, 60 Hz electromagnetic emissions, and patient respiration. Also, an interesting wavelet-based approach has been proposed for ECG signal detection [17], though it lacks ICA's ability to adaptively represent signals with other than fixed basis functions.

This work extends the application of ICA neural networks beyond ECG noise elimination, to the demixing of signal components corresponding to various heart functions. Such demixed components may be more readily associated with abnormal conditions of the heart, even when abnormalities are difficult to detect in the measured signals. Given a sufficient number of ECG sensors, any number of noise sources and actual heart sources can be demixed. One notable potential application of this approach is the automatic detection of the QRS complex for patient monitoring.

2. ECG SIGNALS

Normal ECG signals are known to have various components corresponding to different heart functions [15], as shown in Figure 1. These signal components are generated from electrical activity in the heart to stimulate muscles for pumping blood. The components lead to measured ECG signals in which the major P, Q, R, S, and T waveforms can provide important diagnostic information for the trained physician.

We postulate that abnormal signals also have various components, but some of the heart functions are poor, so that the corresponding components are poor. The difficulty is that signal components are mixed in the actual measured ECG signals. In this case, neither the original source signals nor the exact way in which they are mixed in the body are known. The measured signals are also expected to be corrupted by various noise sources. If we can somehow separate the various source and noise components from ECG signals, it may help in the early detection of heart abnormalities.

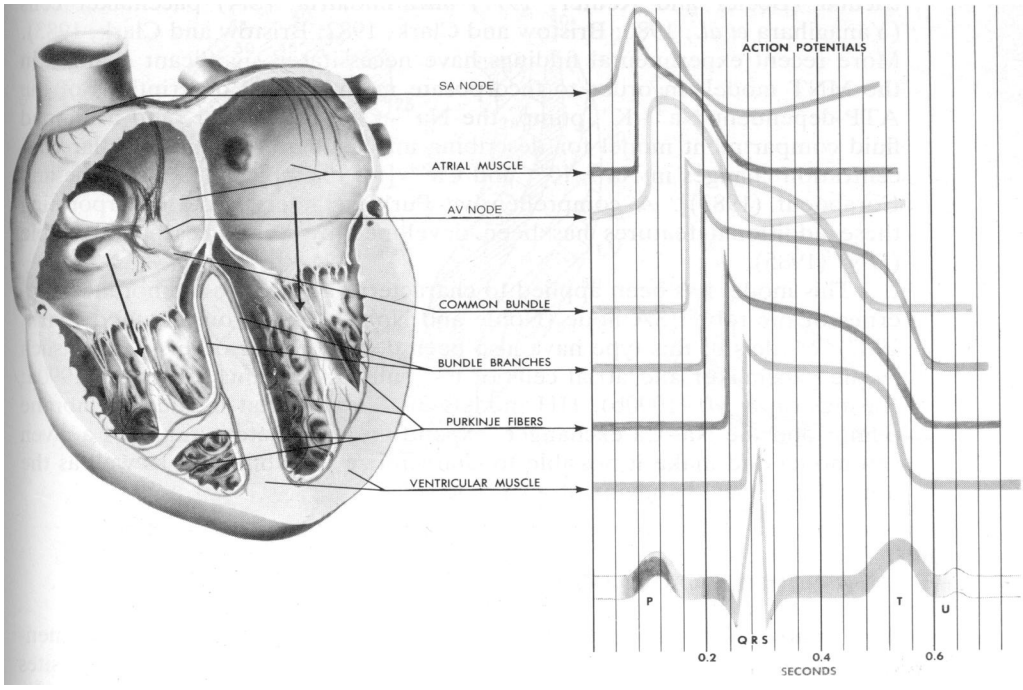

Figure 1. ECG signal components for the healthy heart, which have a typical QRS amplitude of 1-3 mV (reprinted from [15]).

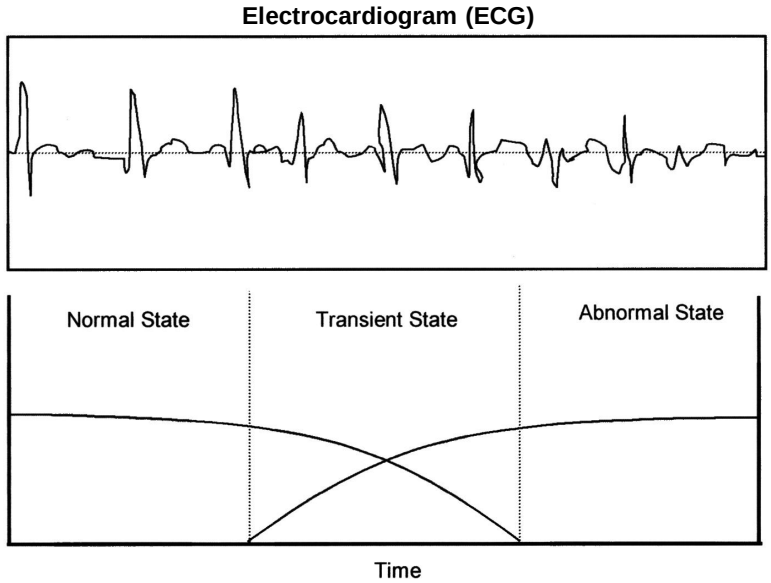

Figure 2. Transient state has both normal and abnormal ECG signal components.

We further envision a scenario in which there is something of a gradual change from normal to abnormal heart condition, as shown in Figure 2. During the transition period, the ECG is composed of both normal and abnormal components. During the early phase of the transition period, abnormal signal components are relatively weak, so that detection of abnormalities in the

measured signals is difficult. But this early phase is the critical time when the patient might be the most responsive to medical treatments.

3. ICA BLIND SEPARATION OF ECG SIGNALS

Given the hypothesis that ECG signals are mixed components, this suggests that ICA via artificial neural networks can demix the individual components [1][3][4][10][16]. The ICA models signals arriving at *m* receivers as a linear sum of *n* signal sources. Therefore, if $\mathbf{s} = [s_1(t), s_2(t), \ldots, s_n(t)]$ is the vector that consists of source signals and $\mathbf{x} = [x_1(t), x_2(t), \ldots, x_m(t)]$ is the vector of the received signals, we have:

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

where **A** is a $n \times m$ matrix of full rank, with $n \geq m$.

The goal of ICA algorithms is to find a matrix **W** that multiplied by **x** can recover the signals from the sources. If we assume that the matrix **A** is a $n \times n$ invertible square matrix, the system output is

$$\hat{\mathbf{s}} = \mathbf{A}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s} = \mathbf{C}\mathbf{s} \tag{2}$$

where, ideally **WA** = **I** (I is the identity matrix), but usually **C** operates a permutation and a re-scale in the vectors. However, for the ICA algorithm to find that matrix **W** the elements of the vector **s** must be *mutually independent*. This means that the joint probability density of the source signals must be the product of the marginal densities of the individual sources, i.e.

$$p(s) = \prod_{i=1}^{M} p(s_i) \tag{3}$$

In most algorithmic derivations, an equal number of sources and sensors is assumed. Furthermore, only up to one source may be Gaussian [16].

The ICA algorithm adjusts the elements of the matrix **W** in order to obtain signals that are the most independent as possible in the vector $\hat{\mathbf{s}}$. For reaching this independence, several algorithms have been derived, involving entropy maximization, mutual information minimization, maximum likelihood, Kullback-Liebler (K-L) divergence minimization and kurtosis maximization or minimization.

The use of K-L divergence is a well-explored strategy that is related to mutual information and entropy. It measures how far the probability density of $\hat{\mathbf{s}}$ is from the probability density of *s*. In a general form, we can state this as

$$l\{p(s), \hat{p}(\hat{s}, \hat{\theta})\} = \int p(s) \log \frac{p(s)}{\hat{p}(\hat{s}, \hat{\theta})} d\hat{s} \tag{4}$$

Therefore, adjusting **W** in order to minimize the contrast function $l\{p(s), \hat{p}(\hat{s}, \hat{\theta})\}$ drives $\hat{p}(\hat{s}, \hat{\theta})$ close to the true density $p(s)$.

This minimization can be carried out by applying a gradient descent method. The gradient descendent method updates the matrix **W** in the opposite direction of the gradient of the contrast function $l\{p(s), \hat{p}(\hat{s}, \hat{\theta})\}$ with respect to the matrix **W**. For this case, usually the elements of **W** are updated by an expression of the form

$$\mathbf{W}_{k+1} = \mathbf{W}_k - \mu_k [\mathbf{I} - N(\hat{s}_k)] \mathbf{W}_k , \tag{5}$$

where $N(\cdot)$ is a non-linear function and μ is the learning coefficient [3]. Bell and Sejnowski [5] suggested the following function for $N(\cdot)$:

$$N(\hat{s}_k) = \tanh(\hat{s}_k) \hat{s}_k^T . \tag{6}$$

This non-linearity tries to shape the sources distribution. If we expand it in a Taylor series

$$\tanh(u) = u - \frac{u^3}{3} + \frac{2u^5}{15} + \ldots \tag{7}$$

we notice that the matrix **W** is adjusted based on maximization and minimization of high-order moments of $\hat{s}$ [5][9].

It should be added, however, that by using the gradient descent approach, we are involved with choices such as the non-linear function and the learning coefficient. A bad choice of those may affect adversely the algorithm behavior [9]. The choice of the non-linear function is related to the sources probability distributions [5]. Despite it being said that ICA algorithms *blindly* find the source signals, a correct choice of the non-linearity and of the sign of μ can improve algorithm convergence for signals with super-Gaussian (kurtosis > 0) or sub-Gaussian (kurtosis < 0) distributions.

In this work, we use the ICA algorithm developed by Hyvärinen and Oja [9]. In their algorithm, Hyvärinen and Oja use the kurtosis as contrast function.

$$\mathrm{kurt}(\hat{s}_i) = E\{\hat{s}_i^4\} - 3(E\{\hat{s}_i^2\})^2 \tag{8}$$

where $E(\cdot)$ denotes expectations. Note that in this approach the kurtosis defines the non-linear function $N(\cdot)$ to be used. Under the constraint $E\{(\mathbf{wx})^2\}=1$, where **w** is a row of **W**, the $\mathrm{kurt}(\hat{s}_i)$ is maximal or minimal when $\hat{s}_i$ is one independent component, i.e, one source signal $\hat{s}_i$. One important difference of the Hyvärinen and Oja's proposal is that, only one IC is estimated at a time. At first, to update the vector **w**, they used the gradient of kurtosis with respect to **w**, or

$$\nabla_w \mathrm{kurt}(\mathbf{wx}) = 4[E\{\mathbf{x}(\mathbf{wx})\}] - 3E\{\mathbf{xx}^T\}\mathbf{w}^T \tag{9}$$

The performance of the stochastic gradient descent approach depends on the learning rate sequence μ_k. Based on this, Hyvärinen and Oja introduced an elegant and efficient fixed-point algorithm for estimating each row **w** of matrix **W** [9]. The fixed-point iteration algorithm is a way carrying out a more reliable and faster learning. Besides, it does not use any learning coefficient μ_k. The fast ICA fixed-point algorithm is defined as

- *Take a random initial vector* $\mathbf{w}(0)$. *Let k = 1;*
- *Let* $\nabla\mathbf{w}(k) = E\{\mathbf{x}(\mathbf{w}(k-1)^T\mathbf{x})^3\} - 3\mathbf{w}(k-1)$. *The expectation can be estimated using a large sample of x vector;*
- *Divide* $\mathbf{w}(k)$ *by its norm;*
- *Repeat the procedure if* $|\mathbf{w}(k) - \mathbf{w}(k-1)|$ *is not close enough to 1. Otherwise, output vector* $\mathbf{w}(k)$.

After the fourth step, the estimated source signal $\hat{s}_j \propto s_i = \mathbf{wx}$ is achieved. To obtain the other independent components, up to a maximum of *n* the algorithm may be run many times as required. However, at each time the estimated component $\hat{s}_j$ should be subtracted from the data vector **x**. As $\hat{s}_j$ is a mixture of the **x** elements, that subtraction implies multiplying $\hat{s}_j$ by a vector, whose elements scale $\hat{s}_j$ to cancel its contribution in each component of the data vector **x**.

4. EXPERIMENTS

For this study, we extracted data from the PhysioBank ECG database [7]. We applied our proposed method to several ECG data sets including "MIT-BIH Arrhythmia," "MIT-BIH Long-Term ECG," "Long Term ST Database," "BIDMC Congestive Heart Failure," and "MIT-BIH Noise Stress Test." Unfortunately, most of the data sets have only two or three ECG leads (sensors). With ICA, the number of sensors limits the number of signal sources that can be blindly separated. The data sets have been annotated by two independent cardiologists, to aid in signal interpretation.

For the ICA algorithm, we used the FastICA Matlab toolbox [6], one of the more popular ICA implementations. We applied ICA to several ECG databases to see the differences between normal and abnormal components in various ECG signals.

Figure 3 is an example from the MIT-BIH Noise Stress Test data set showing a transient state in which there are abnormal signal components, even though abnormalities are not apparent in the measured signals.

After applying ICA to the PhysioBank ECG data, there are some differences between the original ECG and the independent components resulting from blind source separation. Some components are emphasized while others are reduced or missing. As a result, both normal and abnormal signals are significantly changed. However, the results are not completely satisfactory, because there are only two or three measured ECG signals to demix. In Figures 4 and 5, there are three measured signals, and those have more separated components compared to the ECG signals in Figure 3. If there were more measured signals, ICA would likely yield better results.

Here we do not clearly detect the precursor for early warning to prevent the heart failure. We think the reasons are largely the ECG machine circuitry and the insufficient number of source signals. When the ECG data was measured, the instrumentation circuitry likely eliminated some detail information from the heart signals by digital signal post processing. Thus, we were missing information in the ECG database that might be useful in detecting the precursor. If these problems are solved ICA can provide an improved signal representation for detecting both the precursor and QRS complex.

However, as a result of ICA, we can determine whether the ECG is normal or abnormal more easily without the trained doctor's opinion. Some components are more emphasized or some components are either missing or reduced in the ICA blind source separation. Therefore, ICA is a good potential framework for automated heart monitoring.

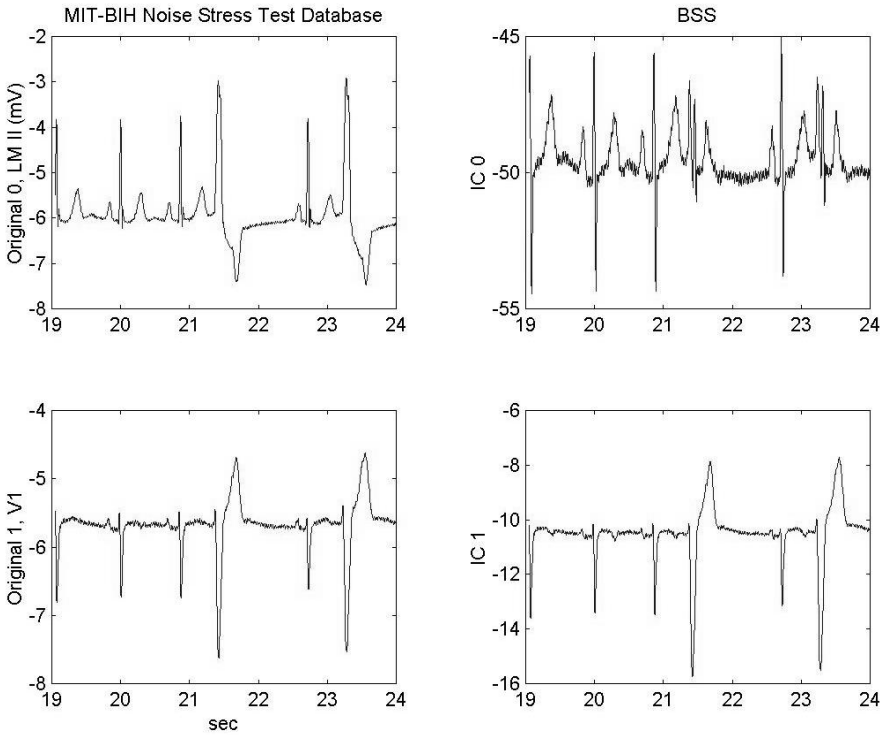

Figure 3. ICA for MIT-BIH Noise Stress Test data set

5. SUMMARY AND CONCLUSIONS

For the first time, independent component analysis is applied to cardiac signals beyond the mere extraction of noise components. In particular, we apply ICA neural networks for the separation of signal components corresponding to individual heart functions, both normal and abnormal. Abnormal signals are more easily detected in the independent components compared to the original measured ECG signals, reducing the need for trained doctors' opinions. Given a sufficient number of high-resolution ECG sensors, ICA neural networks can provide a powerful framework for aided diagnosis and patient monitoring.

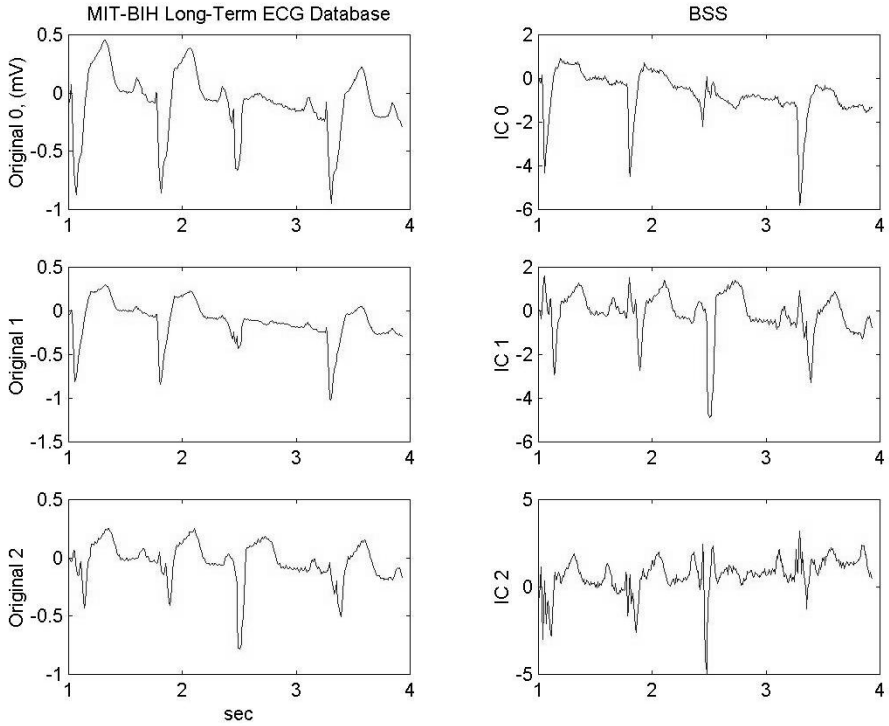

Figure 4. ICA for MIT-BIH Long-Term ECG data set

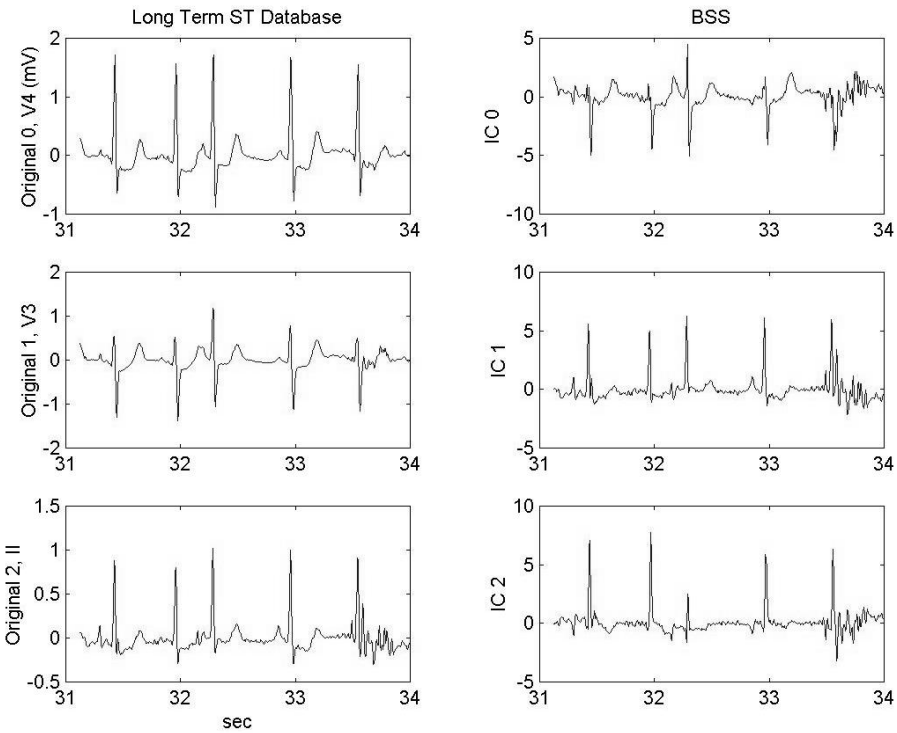

Figure 5. ICA for Long Term ST data set

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