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Blind Source Subspace Separation and Classification of ECG Signals

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***Abstract*— Extracting foetal electrocardiogram (fECG) plays an important role in diagnosing foetus's health. However, in real clinical tests, a clean extraction of fECG is difficult to be obtained, because it is affected by various signals such as mother electrocardiogram (mECG), electromyogram (EMG) derived from the uterus and muscle contractions, the respiration signal, electronic noise, *etc*. Inspired by recent work estimating fECG subspace from a mixed ECG signals using multidimensional independent component analysis (MICA) along with the cyclic coherence (CC), we propose here an approach to separate and classify ECG signals recorded from abdominal and thoracic electrodes of pregnant women. The first step, blind source separation (BSS) is done by applying the joint approximate of Eigen matrices (JADE) algorithm to obtain independent components (ICs). Then continuous wavelet transform (CWT) is adopted for classifying the independent components previously obtained into three subspace components: fetal ECG signals, the mother ECG signals, and the noise. Our experimental results have corroborated the proposed approach using the database DaISy.**

Keywords— Blind Source Separation; ECG; fECG; Continuous Wavelet Transform; MICA

I. INTRODUCTION

Foetal electrocardiogram (fECG) is a very important tool for foetus's heart monitoring. With the aim of helping physicians to make a good diagnosis, it is useful to extract a clean fECG from observed mixed signals.

To extract fECG, Zarzoso et *al* proposed a comparison among blind source separation (BSS) methods based on higher-order statistics (HOS) and windrow's multi-reference adaptive noise cancellation and they conclude that the HOS are more robust [1]. The authors of [2] used blind source subspaces separation (BSSS) to extract fECG and demonstrated the effectiveness of BSSS over classic approaches based on support vector machine technique (SVM) and principal component analysis (PCA), they confirmed that BSSS is a very ambitious approach. More recently multidimensional independent component analysis (MICA) and cyclic coherence for separation and classification of mixed ECG recordings from a pregnant woman have been proposed [3], [4], [5]. To separate fECG and mECG, FastICA and a pre-processing wavelet tool is proposed in [6], [7]. In [8] and [9] the tensor decomposition and the Kalman filter have been employed to extract fECG. The applying various BSS algorithms, in order to separate fECG and mECG signals, authors of [10] developed comparative study. The maxima modulus of wavelet is introduced to extract fECG from the composite abdominal signal [11]. By using wavelet decomposition, the authors of [12] extracted fECG by subtracting mECG signal from mother's abdomen ECG signal (AECG).

Without major information about the sources and the mixture, BSS methods try to extract the original signals (called sources) from mixed observed signals (called mixture signals). In this manuscript, first, joint approximate of Eigen matrices (JADE) algorithm [13] is used in order to extract independent components (ICs), then, we use Continuous Wavelet Transform for classifying ICs into three groups; fECG, mECG and noise.

The manuscript is organised as follows. Section II introduces the blind sources separation problem and the multidimensional independent component analysis concept, than a presentation of continuous wavelet transform and the percentage of energy for each coefficient was achieved in section III. The simulation results are displayed in section IV. Finally a conclusion is drawn in section V.

II. THE MICA CONCEPT FOR BLIND SOURCE SEPARATION

A. Blind source separation

Blind separation of sources problem was firstly introduced by Jutten and Herault [14] to study the biological signals. Later on, several authors interested and developed algorithms in various areas [15]. In biomedical applications, BSS become promising approaches, used to remove ECG artifacts [16], to eliminate ocular EEG artifacts [17], separate the EEG, EMG, EOG [18], …

The main idea behind the BSS problem is to find unknown sources from only the observing mixture of them [19]. The mixture may be instantaneous, convolutive, linear or nonlinear. The instantaneous linear mixture is the most used, for further details see [19], [20]. For a linear instantaneous mixture, the model is given by the following equation:

$$y(t) = Az(t) \qquad (1)$$

Where $z(t)$ stands for the source vector, A is a mixing matrix, and $y(t)$ becomes the observation vector (i-e mixture signals).

In BSS, three main assumptions are widely used:

i) The sources are supposed statistically independent of one another.

ii) A is a full rank matrix, and generally, authors consider that the number of sensors is equal or great than the number of sources.

iii) At most one of the sources can be a Gaussian signal.

The transfer from bioelectric current source to skin electrode can be assumed linear. On the other hand the frequency at which the bioelectric source signals are sampled (250-500 Hz) can be considered as law, taking into account the high propagation velocity of the electrical signals. Hence the cutaneous potential measurements can be considered as instantaneous linear mixtures [21].

B. *Multidimensional ICA concept*

Multidimensionnal ICA is a generalization of the independent components analysis (ICA) concept, it is introduced by Cardoso in [22]. Later on, many approaches have been proposed to apply multidimensional ICA for biomedical signals [4], [5], [23], [24], [25]. A MICA decomposition, can be done by two steps:

i) Execute an ICA algorithm in order to obtain estimates of monodimensional signals sources.

ii) Gather similar multidimensional components as a part of original signal.

III. METHODS

A. *The JADE algorithm*

In order to separate the mixed signals, we use Joint Approximate Diagonalization of Eigen-matrices [13] (JADE) algorithm, which can be described by four steps:

1- Find the covariance matrix R_Y and compute a whitening matrix B.

2- Find the 4th-order cumulants of the whitened signals then compute the eigenvalue λ_r and the Eigen matrices M_r of the cumulants.

3- Jointly diagonalize $\lambda_r M_r$ by a unitary matrix U.

4- Compute the separation matrix: $W = B^{\#}U$.
Where $B^{\#}$ denotes the pseudo inverse of B.

B. *Continuous wavelet transform*

Wavelets are a mathematical tool which is used in several fields, we are interested in work done in the biomedical field. The authors of [26] used the wavelet detail coefficients for the accurate detection of different QRS morphologies in ECG. In medical magnetic resonance imaging, a multifractal analysis based on wavelets for texture classification is applied [27].

The continuous wavelet transform (CWT) of a signal $x(t)$ is the projection of this signal onto the family of wavelet daughter $\Psi_{\tau,s}(t)$. In other words, the CWT is defined as the inner product between $x(t)$ and $\Psi_{\tau,s}$ as follows [28]:

$$CWT(x(t)) = X_\Psi(\tau,s) =< x(t), \Psi_{\tau,s}(t) > \quad (2)$$

Where $$\Psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\Psi\left(\frac{t-\tau}{s}\right) \quad (3)$$

- $\Psi(\mathrm{t})$ stands a continuous function called mother wavelet.
- τ represents a translation parameter.
- s is a scale parameter. Note that, if s is small, than higher-frequency components can be analysed, and when it is larger lower-frequency components can be analysed.

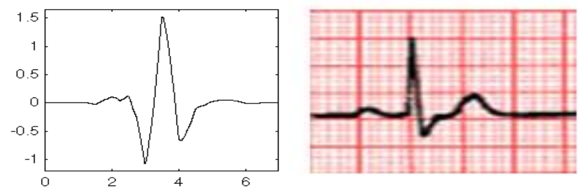
Replacing (3) in (2), then (2) becomes:

$$X_\Psi(\tau,s) = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\Psi^*\left(\frac{t-\tau}{s}\right) \quad (4)$$

Where * denotes the complex conjugate.

The CWT can generate many wavelet coefficients $X_\Psi(\tau,s)$ as functions of scales and positions. Wavelet families include Daubechies, Symlet, Coiflet, Biorthogonal, Morlet, *etc*.

In our application, we used the Symlet wavelet transform, which is similar in shape to ECG signal (see Fig. 1).



(a) (b)

Fig. 1 The Symlet's wavelet shape (a), the ECG shape (b).

C. *Energy of wavelet coefficients*

The energy E of a continuous-time signal $w(t)$ is defined as:

$$E =< w(t), w(t) \geq = \int_{-\infty}^{+\infty} |w(t)|^2 dt \quad (5)$$

After computing wavelet coefficients $X_\Psi(\tau,s)$, we calculate the energy $E_{X_\Psi(\tau,s)}$ for each coefficient.

$$E_{X_\Psi(\tau,s)} = \iint_{-\infty}^{+\infty} | X_\Psi(\tau,s)|^2 \ d\tau ds \quad (6)$$

The percentage of energy is given by:

$$PE_\Psi(\tau,s) = \frac{100|X_\Psi(\tau,s)^2|}{E_{X_\Psi(\tau,s)}} \quad (7)$$

This percentage is computed in order to classify the independent components (ICs).

IV. SIMULATION RESULTS

In our simulation, we use a real signals which provided by the database DaISy [29]. The signals contain non-invasive electrocardiogram of 2500 points, recorded from 8 electrodes located on a pregnant woman's skin (Fig.2). The sampling frequency whose the signals were recorded is 500 Hz with a total sampling time of 5 seconds.

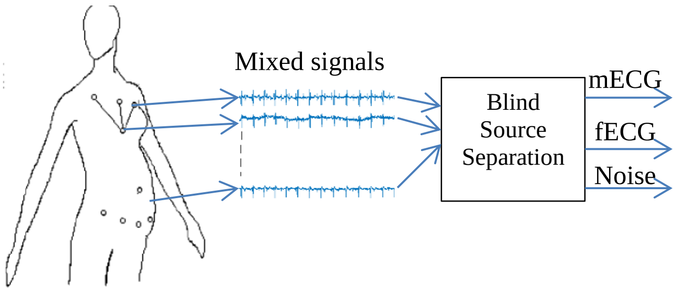


Fig. 2 ECG signals of a pregnant woman

Fig. 3 shows the eight channels of cutaneous data recordings. Channels 1-5 (Ab1,…,Ab5) indicate abdominal signal, where the contribution of the foetal heartbeats is significant. Channels 6-8 (Th1,…,Th3) give further information on the mother heartbeats (the recordings taken from the mother's thorax). But all channels are a mix of mECG, fECG and noises as it is emphasis previously. At first, we applied JADE algorithm in order to separate the observations into independent components ICs. The separation results are shown in Fig. 4.

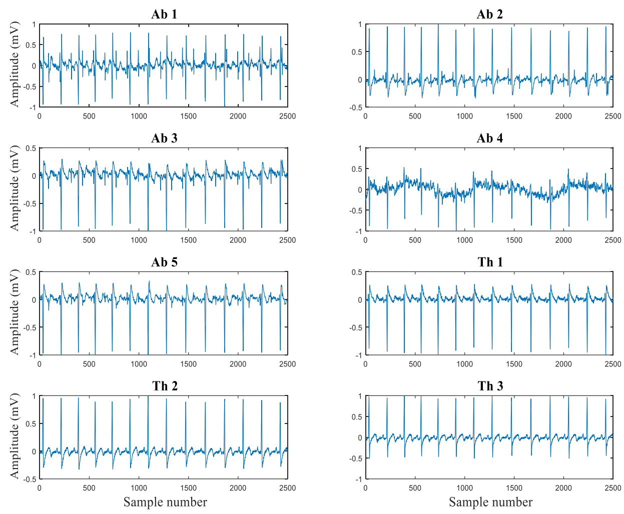


Fig. 3 Cutaneous electrode recording from a pregnant woman

In order to classify the independent components ICs previously obtained into three multidimensional components, the continuous wavelet transform is applied of each ICs. The following figures show the wavelet coefficients on two dimension (time-scale). We can roughly observe three groups of signals: the group {IC1, IC2, IC3, IC7} (Fig. 5 (a)) have low frequency (60-70 Hz) which should be mainly related to mother's ECG, the second group {IC5, IC8} (Fig. 5 (b)) contains signals with high frequency (130-180 Hz) which can related to foetus ECG, while the remaining group contain artifacts and noise signal {IC4, IC6}(Fig. 5 (c)). Not that in the last group, IC4 represents a respiration signal (very low frequency 4-10 Hz).

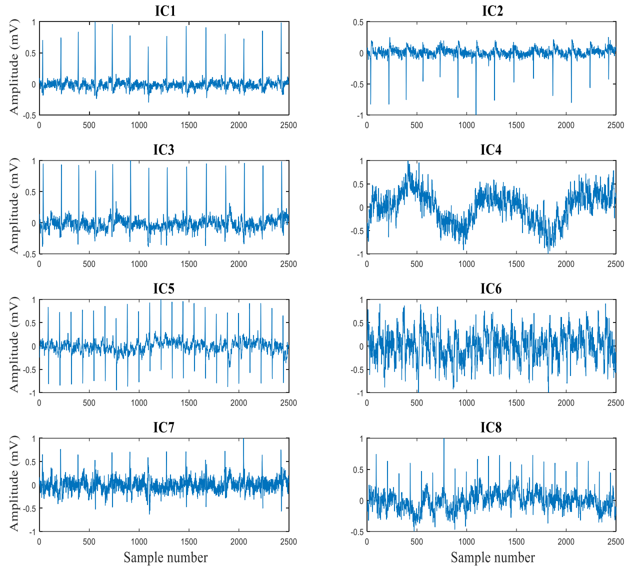
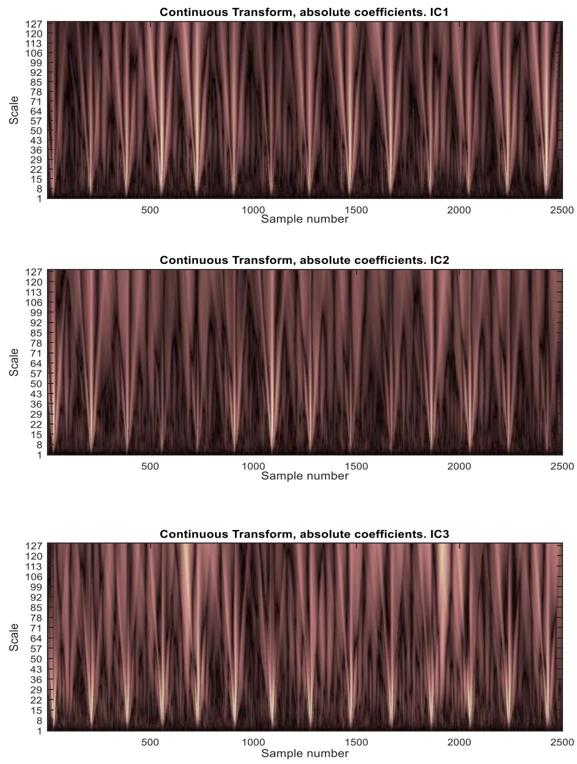
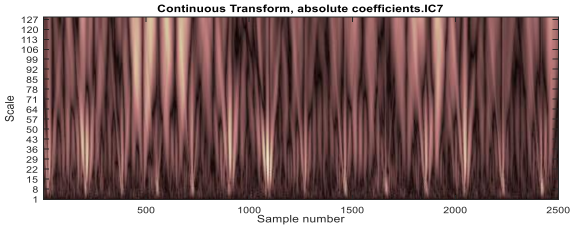
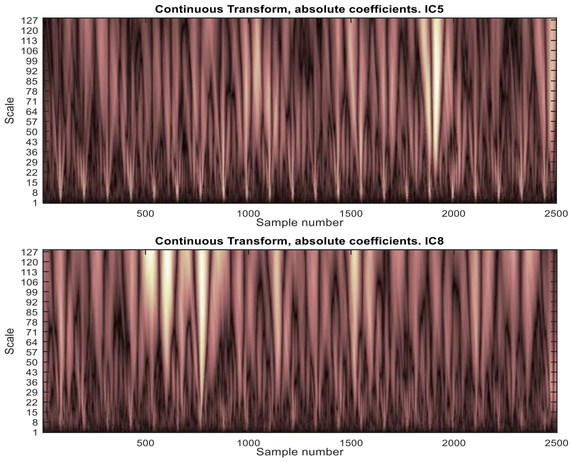


Fig. 4 Estimates source signals obtained by JADE

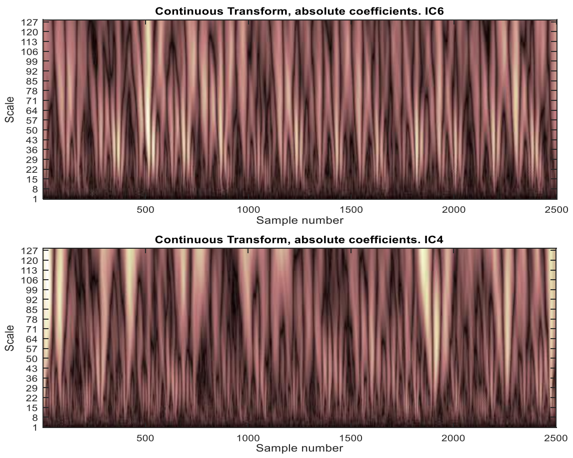




(a) mECG subspace {IC1, IC2, IC3, IC7}



(b) fECG subspace {IC5, IC8}

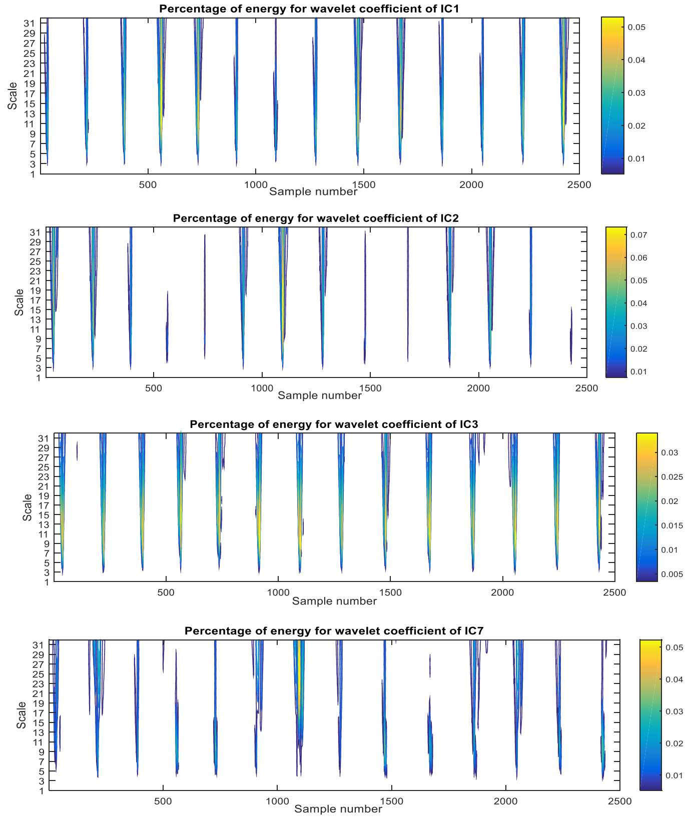


(c) Noise subspace {IC4, IC6}

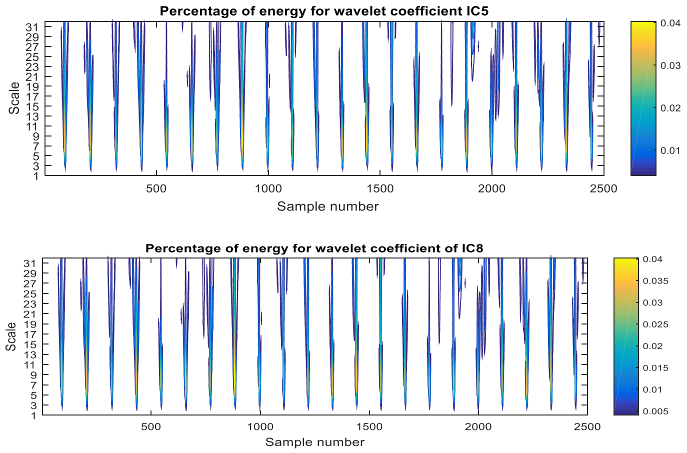
Fig. 5 Wavelet coefficients of eight independent components from JADE

Using continuous wavelet coefficients, the classification is not appropriately done, moreover it is quite difficult to distinguish among three subspaces, what's why we compute the percentage of energy for each wavelet coefficient, which are obtained by applying a continuous wavelet transform for independent components ICs.

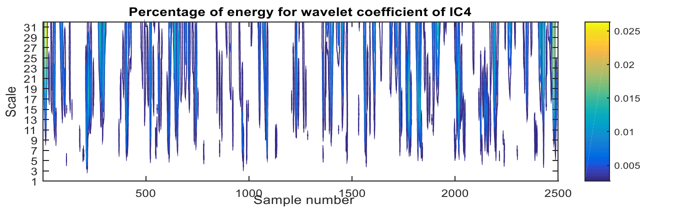
Fig.6 shows clearly three subspaces. mECG subspace = {IC1, IC2, IC3, IC7}; fECG subspace = {IC5, IC8}; noise subspace = {IC4, IC6}.

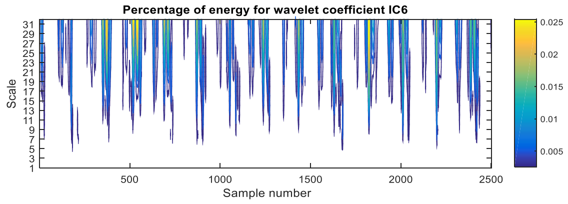


a) mECG Subspace {IC1, IC2, IC3, IC7}



b) fECG subspace {IC5, IC8}





c) Noise Subspace {IC4, IC6}.

Fig. 6 Percentage of energy of each wavelet coefficient

V. Conclusions

In this work, we propose a classification procedure based on continuous wavelet transform of independent components from maternal ECG recordings. After separating the mixed signals using JADE algorithm into independent components, we compute coefficients wavelet of each ICs, the simulation results show that we can divide ICs into three subspaces. Moreover the method is very promising by computing the energy of the wavelet coefficients, thus we can easily classify the ICs, and the results clearly show the three groups fECG, mECG and noise.

In near future work, we will investigate wavelet packet decomposition along with MICA and other BSS technics.

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