Fetal ECG Extraction Using Hybrid BSS Techniques

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Abstract

In the task of extracting the fetal ECG from abdominal ECG, often blind source separation is used as an intermediate step. To solve this problem is generally employed PCA and ICA. The COMBI and MULTI-COMBI algorithms offer novel schemes for combining PCA and ICA, enabling exploit the strengths of both techniques. In this work, the performance of the algorithms COMBI, MULTICOMBI, EFICA and traditional JADE algorithm are compared. We used a semi-synthetic database. In all case, it is found that the COMBI and MULTICOMBI algorithms show better performance than the JADE, and EFICA algorithms.

1. Introduction

To achieve separation of fetal and maternal electrocardiograms, BSS is the most widely used technique for extracting the FECG [1]. In this paper we introduce COMBI [2] and MULTICOMBI [3] algorithms based on hybrid BSS for extracting FECG from the AECG. We compare the performance of COMBI and MULTICOMBI algorithms against JADE [4], WASOBI [5] and EFICA [6] using a semi-synthetic database.

2. Methods

2.1. Blind Source Separation

To solve BSS problem, different methods have been proposed mainly based on Principal Component Analysis (PCA) and Independent Component Analysis (ICA). In PCA methods stands SOBI algorithm [7] and its improved version WASOBI, and in ICA method stands the FastICA algorithm [8] and EFICA. ICA-based methods are the most used for the analysis of AECG because it is considered that the sources are predominantly non-Gaussian and statistically independent of one another.

2.2. Combi and Multicombi Algorithms

Under certain conditions, WASOBI and EFICA are asymptotically optimal. WASOBI only take advantage of time-structure, disregarding the statistical distributions of the sources, whereas EFICA can only take advantage of non-Gaussianity of the sources, ignoring any time-structure. However, realistic mixtures are many times compound of sources which present both diverse time-structure and non-Gaussianity, rendering WASOBI and EFICA severely suboptimal. Algorithms COMBI and MULTI-COMBI offer novel schemes for combining WASOBI and EFICA, enabling exploit the strengths of both techniques. In the context of biological signals such algorithms have been applied to EEG signals [9] and fMRI signals [10], but to date it is not known that these algorithms have been applied in the task of extracting the FECG from the AECG.

To verify a good degree of separation, is defined $\mathbf{G} = \mathbf{WA}$ as the gain matrix. For a perfectly estimated de-mixing matrix, **W, G** is equal to its identity matrix. The performance of blind-source separation algorithms is usually measured by the interference over signal ratio matrix, $\mathbf{ISR}_{kl} = \mathrm{G}_{kl}^2/\mathrm{G}_{kk}^2,\ k, l = 1,2,\ldots,\mathrm{d}$, where k and l denote the observed and estimated sources, and d is sources number. However, the original mixing matrix, **A**, is not generally known for real data sets.

EFICA requires a user-defined choice of a set of nonlinear functions $\mathrm{g_k}(.)$, for extracting each of the sources. Then, ISR matrix for the EFICA algorithm can be approximated by $ISR_{kl}^{EF} \cong \frac{1}{N}\frac{\gamma_k(\gamma_l+\tau_l^2)}{\tau_l^2\gamma_k+\tau_k^2(\gamma_l+\tau_l^2)}$, where $\gamma_k = \beta_k - \mu_k^2$, $\mu_k = \mathrm{E}[\hat{s}_k g_k(\hat{s}_k)]$, $\tau_k = |\mu_k - \rho_k|$, $\rho_k = \mathrm{E}[g_k'(\hat{s}_k)]$, and $\beta_k = \mathrm{E}[g_k^2(\hat{s}_k)]$. E[.] denotes the expectation operator and $g_k'(.)$ denotes the derivative of $g_k(.)$, and $\hat{s}_k$ is the *k*th observed signals of $\mathbf{s}$ [11].

WASOBI is based on approximate joint diagonalization of several (say M) time-lagged estimated correlation matrices, $\widehat{\mathrm{R}}_x[\tau] = \frac{1}{\mathrm{N}-\tau}\sum_{\mathrm{n}=1}^{\mathrm{N}-\tau}[\mathrm{n}]\mathrm{x}^{\mathrm{T}}[\mathrm{n}+\tau]\,, \tau = 0, \ldots, \mathrm{M}-1$, where x[n] denotes the nth column of **x**. If all sources are Gaussian AR of order $\mathrm{M}-1$, then under asymptotic conditions the ISR matrix is $\mathrm{ISR}_{kl}^{\mathrm{WA}} \cong \frac{1}{\mathrm{N}}\frac{\phi_{kl}}{\phi_{kl}\phi_{lk}-1}\frac{\sigma_k^2 R_l[0]}{\sigma_l^2 R_k[0]}$, where $\phi_{kl} =$

$\frac{1}{\sigma_k^2}\sum_{i,j=0}^{M-1} a_{il}a_{jl}R_k[i-j]$, k and l denote the observed and the estimated sources, σ_k^2 is the variance of the innovation sequence of the kth source, $\{a_{il}\}_{i=0}^{M-1}$ are the auto-regression coefficients of the lth source, and $R_k[m]$ is the autocorrelation of the kth source at time lag m [12].

In COMBI, the ISR matrices are obviously unknown. However, it is possible to substitute these with the mean ISR, $\widehat{ISR}^{WA}$ and $\widehat{ISR}^{EF}$. COMBI apply both EFICA and WASOBI to $\mathbf{x}$ and estimate $\widehat{ISR}^{WA}$ and $\widehat{ISR}^{EF}$ select for each source the reconstructed version that has the best total ISR of the two. This basic selection approach can then be turned into a successive scheme, such that in each iteration only the "best" separated sources are "accepted," and the remaining signals (which are still weakly separated mixtures of the remaining sources) are subjected to an additional iteration of separation and selection [12].

MULTICOMBI uses a clustering technique based on "multidimensional component". A multidimensional component is a cluster of signal components that can together be well separated from the other components in the mixture, yet are difficult to separate from one another. For EFICA, only components that have (nearly) Gaussian distributions might form such a cluster, hence at most one such cluster may exist. For WASOBI, any components sharing similar correlation structures (i.e., power spectra) are hardly separable from one another, but may be easily separated as a cluster, hence several such clusters might coexist [11]. MULTICOMBI uses this clustering technique in which both algorithms, EFICA and WASOBI, are run on the set of unseparated sources $\hat{\mathbf{x}}$ and their $\widehat{ISR}^{EF}$ and $\widehat{ISR}^{WA}$, are estimated. The signals are then clustered depending on whether their specific ISR_{kl} is lower for the EFICA or WASOBI case. Then, the process is repeated until all clusters are singletons, ie. only contain one signal per cluster, and the signals are hence optimally separated [13].

2.3. Semi-synthetic Database

We built a semi synthetic database [14],[15] as:

$$X_{AECG} = \alpha H_m X_{MECG} + H_f X_{FECG} + \beta n \qquad (1)$$

X_{MECG} and X_{FECG} are 3-D sources representing the maternal and fetal cardiac components, H_f and H_m are the volume conduction transfer matrices for the mother and fetus respectively. In this model, the maternal signal $H_m X_{MECG}$ is assumed as interference while $\mathbf{n}$ is assumed as noises for the fetal signal $H_f X_{FECG}$. The parameters α and β control the signal to interference ratio (SIR) and signal to noise ratio (SNR). To model $\mathbf{n}$ can be selected from Gaussian white noise or pink noise. The number of rows of H_f and H_m can be adjusted as the number of leads required to simulate the AECG. It is also possible to model the relative fetal position respect to the axes maternal body introducing specific angles between the subspaces of the matrix columns H_f and H_m. A three-second segment of eight maternal channels, and result when MULTICOMBI algorithm is used, is shown in Figure 1.

2.4. Performance parameters

The parameters α and β in (1) control signal to interference ratio (SIR) and signal to noise ratio (SNR), defined as $SIR = 10\log_{10}\frac{\sum_{n=1}^{L}(X_{FECG})^2}{\sum_{n=1}^{L}(X_{MECG})^2}$ and $SNR = 10\log_{10}\frac{\sum_{n=1}^{L}(X_{FECG})^2}{\sum_{n=1}^{L}(n)^2}$. As performance parameter the signal to error ratio (SER) is used. The SER is a measures of fetal signal quality before extraction. SER is calculated as: $SER = 10\log_{10}\frac{\sum_{n=1}^{L}(X_{FECG})^2}{\sum_{n=1}^{L}(X_{FECG\_OBS}-X_{FECG})^2}$, where X_{FECG} is the desired signal and $X_{FECG\_OBS} - X_{FECG}$ is the error. Here X_{FECG_OBS} is the estimated source signal and X_{FECG_OBS} and X_{FECG} should be at the same energy level and phase while calculating the error.

3. Experiments and results

3.1. Database

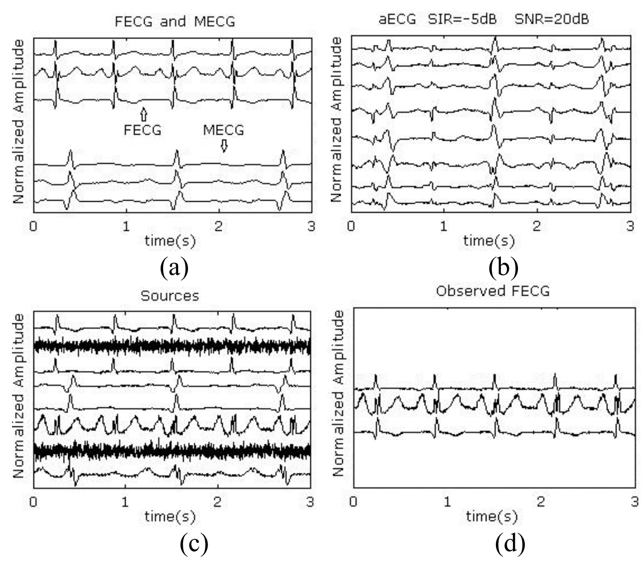


Figure1. A three-second segment of eight maternal channels, and result when MULTICOMBI algorithm is used. Figure 1-a, FECG and MECG used to synthesize an AECG. Figure 1-b, the AECG resulting of applying the method, SIR is -5dB, and SNR is 20 dB, white noise. Figure 1-c, result of applying the MULTICOMBI algorithm. Figure 1-d, FECG synthesized. In this example, the SIR achieved is 10.8 dB.

In this paper we used a database built according to (1). X_{MECG} y X_{FECG} were taken from diagnosis database PTB [16] from orthogonal leads Vx, Vy, y Vz. PTB has a sampling rate of 1000 Hz.

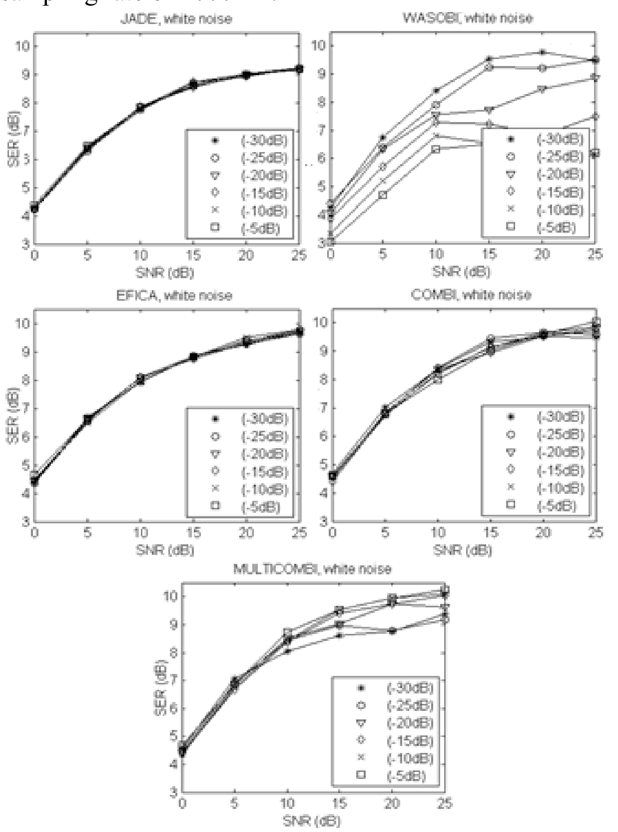


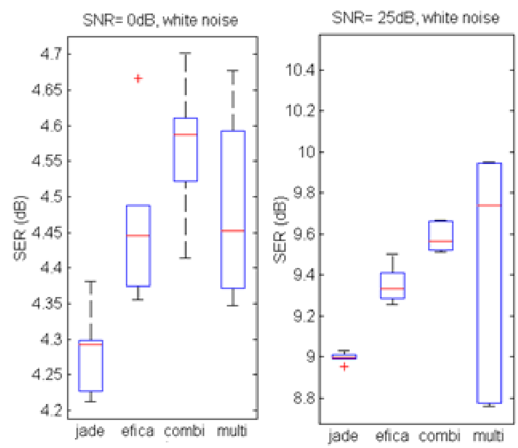
Figure 2. Signal to error ratio (SER) vs. Signal to noise ratio (SNR) for -30 a -5 dB Signal to interference ratio (SIR), presence of white and pink noise, for JADE, WASOBI, EFICA, COMBI and MULTICOMBI algorithms. Each simulation point is an average of 20 trials

The signals were pre-processed for baseline wander removal and low pass filters with cutoff frequency 100 Hz. To build a database of 26 records AECG, 52 records from healthy subjects were used, half of which were randomly selected, represent X_{MECG}, and the remaining were re-sampled to 500 Hz to simulate fetal sources X_{FECG}, because the fetal heart rate is typically twice the fetal heart rate. In order to get eight channels of abdominal observations X_{AECG} in (1), were selected random matrix H_f and H_m of 8x3 with angles between the sub-spaces of the column below 40 °.

SIR values were swept in the range of -5dB to -30dB, which are in the range of actual values. SIR = 0 dB, indicates that the FECG has a higher power than the MECG which is not real, therefore is excluded from the analysis. SNR values were swept in the range of 0dB to 30dB. For each noise type and for each algorithm, all possible combinations between the values of SNR and SIR are investigated to 20 repetitions. The step is 5 dB. In each repetitions Hm, Hf and noise are varied randomly. SER is the average obtained for 20 repetitions. At each step of the process the signals are normalized for purposes of calculating the SIR, SNR and SER. All simulations were carried out on data segments of 10 seconds with a sampling frequency of 500 Hz.

3.2. Results

The AECG resulting of applying the method according to (1) it is processed for JADE, WASOBI, EFICA, COMBI and MULTICOMBI to estimate the FECG sources. Each channel of estimated FECG sources, is compared by the SIR with each channel of X_{FECG}. Then, the three signals with SIR greater are considered the FECG estimated, X_{FECG_OBS}. The higher SIR calculated, is averaged with the results of the remaining 19 repetitions in which the noise, Hf and Hm matrix, are changed randomly. The resulting SIR is stored. The SER obtained by each algorithm for different combinations of SNR and SIR is shown in Figure 2 for white noise. Each curve corresponds to a value of SIR in the range -30 to -5 dB.



(a) (b)

Figure 3. Box plot showing the mean SER values for JADE, EFICA, COMBI y MULTICOMBI algorithm. (a) Presence of high noise levels, SNR 0dB. (b) Presence of low noise levels, SNR 25 dB.

As expected, for high values of noise low SER values are obtained, while for low values of noise high SIR values are obtained. Except WASOBI and MULTICOMBI to a lesser degree, a behavior roughly constant regarding SIR exhibit algorithms analyzed.

To visualize the effect of dispersion, the mean SER for SNR = 0dB and for SNR = 25dB is shown in Figure 3 respectively. Figure 3a shows the values of SER in presence of high noise levels, SNR 0 dB, white noise. In this case the COMBI algorithm has the highest median. Figure 3b shows the values of SER in the presence of low levels of noise, SNR 25 dB, white noise. In this case the MULTICOMBI algorithm has the highest median but also the highest dispersion. Figure 4 shows the FECG real vs FECG observed for JADE, WASOBI and MULTICOMBI.

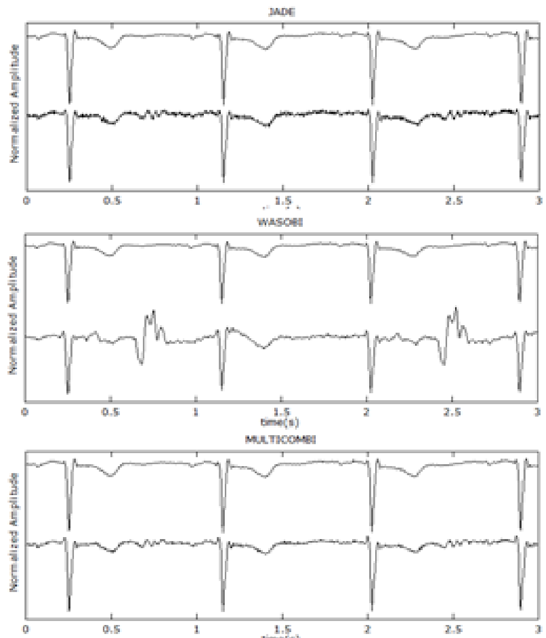


Figure 4. FECG real vs FECG observed, SIR= -20dB & SNR 25 dB white noise, JADE (11.1), WASOBI (6.4) and MULTICOMBI (12.6) (SER in dB).

4. Conclusions

In this paper, we have evaluated five algorithms BSS based, in a semi-synthetic database in the problem to extract the FECG.

COMBI and MULTICOMBI show a slightly better results as compared with ICA algorithms.

The WASOBI algorithm exhibits the worst performance, but combining both WASOBI and EFICA in COMBI and MULTICOMBI algorithms, the strengths of both techniques are exploited exhibiting better performance, although not as expected.

MULTICOMBI present more dispersed results than COMBI results. We think the clustering scheme needs to be optimized for the task of separating the sources in the AECG.

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