Real-Time Back-Projection of Fetal ECG Sources in OL-JADE for the Optimization of Blind Electrodes Positioning

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Abstract

Fetal ECG (FECG) extraction from non-invasive biopotential recordings is strongly affected by the intensity of the FECG contribution to the input signals. The higher the FECG contribution the higher the SNR and consequently the quality of the separation. The definition of a subject-specific good electrodes positioning is an open issue.

In this paper we present a technique based on the fetal ECG extraction algorithm OL-JADE, which tries to invert the whole blind extraction process only for the FECG estimated sources in order to estimate the FECG power at the electrodes. Due to the recursive sample-by-sample nature of the whitening stage of OL-JADE, an approximated Least Squares solution has been introduced in the back-projection scheme revealing adequate performance. An optimized version of the proposed method has been integrated with OL-JADE on a floating point DSP, guaranteeing the respect of the real-time bound.

1. Introduction

Non-invasive fetal electrocardiogram (FECG) extraction aims to achieve the fetal heart electrical activity from the signals picked up by means of electrodes placed on the mother's body. Being the FECG a weak signal embedded in a mixture of stronger interferences, the higher the FECG contribution at the electrodes the higher the Signal to Noise Ratio (SNR) and then the separation quality. Despite the quite rich literature in the field, the problem of a signal acquisition able to emphasize the FECG contribution has been overlooked as opposed to the development of new signal processing algorithms. The robustness with respect to the electrodes positioning of Independent Component Analysis (ICA) techniques, compared to other methods [1], has not fostered the research in this direction. Only a few works deals with signal acquisition and electrodes positioning (e.g. [2, 3]), in some cases selecting a minimal subset of electrodes from a redundant one [4].

In this paper we address the problem of estimating the FECG power contribution at the electrodes in real-time using the OL-JADE algorithm [5]. In principle, a dependable information in this sense could be used to iteratively move a small set of electrodes in order to have at least 2 electrodes with adequate FECG contribution, still providing a different information with each other in order to preserve the identifiability of the ICA model [6]. FECG average power estimation can be regarded as a back-projection problem, addressed in different biomedical fields, including the FECG processing [1,2], for other purposes than the optimization of the separation process. An estimate of the FECG average power at the electrodes could be achieved "inverting" the blind extraction process only for the estimated FECG sources. Since the OL-JADE on-line process cannot be exactly inverted due to its recursive whitening stage, we demonstrate the possibility of achieving anyway an "inverse" of such process as a Least Squares (LS) solution. We show how this approach is effective in producing a power ranking of the FECG contributions at the electrodes in real-time on a floating point DSP.

2. Methods

ICA assumes that the linear instantaneous model $\mathbf{x} = \mathbf{A}\mathbf{s}$, describing the combination of the sources $\mathbf{s}$ giving rise to the observed signals $\mathbf{x}$, can be solved for $\mathbf{s}$ knowing only a realization of $\mathbf{x}$ and some statistical properties about the sources $\mathbf{s}$. The solution is provided up to the permutation and scaling ambiguities [6], the latter stating that the variances of $\mathbf{s}$ remain unknown. Two-stage ICA algorithms estimate an unmixing matrix $\mathbf{A}^{-1} = \mathbf{R} \cdot \mathbf{W}$ in 2 steps, respectively providing a whitening matrix $\mathbf{W}$ for the decorrelation of the observed mixtures and a rotation matrix $\mathbf{R}$ able to emphasize the independent components.

The power contribution of the source s_j is embedded into the whitening matrix $\mathbf{W}$, but it is still possible to estimate it in every input channel as the sample variance, inverting the separation process only for that source:

$$x_i = \sum_j a_{ij} s_j \tag{1}$$

where i spans from 1 to the number of input signals N. Such an approach takes the form of a *back-projection* at the electrodes of the FECG sources. It has been used in the past to try to understand the position of the fetus [2] or for comparative purposes [1] but, to the best of our knowledge, not to define a subject-specific position able to optimize the FECG contribution at the electrodes in order to improve the separation quality.

OL-JADE [5], is a block-on-line ICA method based on the batch JADE algorithm [7]. As the original one, it exploits a 2-stage model from which it maintains the second stage (working on a sliding window of 1024 samples/channel, with 75% overlap). Among the different strategies implemented in order to limit the presence of permutations, there is the choice of a recursive sample-by-sample whitening inspired from [8]. In this way, this stage becomes a crucial point in the algorithm, partially responsible to solve both the ICA ambiguities. The centered data are whitened as $\mathbf{z}(t) = \mathbf{W}_t \cdot \mathbf{x}(t)$, where $\mathbf{x}(t)$ is an array of samples taken from the multi-channel input stream at the sampling instant t, and $\mathbf{z}(t)$ the corresponding whitened samples. The whitening matrix $\mathbf{W}_t$ undergoes a serial update as $\mathbf{W}_{t+1} = \mathbf{W}_t - \lambda_t \cdot \mathbf{H}(\mathbf{z}(t)) \cdot \mathbf{W}_t$, solved in OL-JADE [5] as in the original formulation [8].

In this case, it is not possible to invert the whole procedure exactly. In fact, whether it is possible to easily obtain $\mathbf{R}^{-1}$ for a block of 256 samples/channel, because the $\mathbf{R}$ matrix is orthogonal, so that $\mathbf{R}^{-1} = \mathbf{R}^T$, for the same block of data 256 matrices $\mathbf{W}_t$ are available, which cannot lead to the identification of a single $\mathbf{W}^{-1}$ matrix for the whole block in closed form. We solved this problem finding a matrix $\widehat{\mathbf{W}}^{-1}_{N\times N}$ from the inverse problem $\mathbf{X} = \widehat{\mathbf{W}}^{-1} \cdot \mathbf{Z}$, where both the 256 samples/channel input (centered) block $\mathbf{X}_{N\times 256}$ and sample-by-sample whitened block $\mathbf{Z}_{N\times 256}$ are known. Transposing both members we have $\mathbf{Z}^T \cdot (\widehat{\mathbf{W}}^{-1})^T = \mathbf{X}^T$, which can be easily interpreted as:

$$\mathbf{Z}^T \cdot (\widehat{\mathbf{W}}^{-1})^T = \mathbf{Z}^T \cdot [\mathbf{w}'_1|\cdots|\mathbf{w}'_N] = [\mathbf{x}'_1|\cdots|\mathbf{x}'_N] \quad (2)$$

where the column vectors $\mathbf{x}'_i$ represent a 256-sample block of the i-th centered input mixture, i.e. the i-th row of $\mathbf{X}$. In this inverse problem, (2) states that, for every block of 256 samples/channel, the whole block of whitened mixtures contributes by means of the unknowns $\mathbf{w}'_i$, corresponding to the i-th row of $\widehat{\mathbf{W}}^{-1}$, to the i-th input channel $\mathbf{x}'_i$. The problem is now decomposed into N simpler ones $\mathbf{Z}^T \cdot \mathbf{w}'_i = \mathbf{x}'_i$, which can be solved in parallel finding an LS solution, since the systems are overdetermined having 256 equations and only N unknowns (with $N \ll 256$). We solved this problem by means of the associated normal equations:

$$\mathbf{Z} \cdot \mathbf{Z}^T \cdot \mathbf{w}'_i = \mathbf{Z} \cdot \mathbf{x}'_i \quad (3)$$

It is worth to note how the matrix of the system is now $N \times N$, which is advantageous for a limited memory embedded system. The solution of (3) exist since $\mathbf{Z} \cdot \mathbf{Z}^T$ is not singular if $\mathbf{Z}^T$ is full rank, and this is assumed by hypothesis because otherwise the implicit ICA constraint about the linear independence of the N whitened signals could not be verified. Compared to the QR factorization, the chosen method allows to reduce the computational complexity while preserving a comparable accuracy.

3. Results

To evaluate the correctness of the proposed methodology we used real and artificial mixtures of real signals. The real mixtures (by courtesy of Prof. L. De Lathauwer) consist of 5 abdominal leads and 3 thoracic ones, 60s long, sampled at 250Hz. The artificial ones are generated multiplying by a unique random mixing matrix 4 real signals, 50s long, taken from the MIT-BIH Polysomnographic Database [9, 10] and representing the maternal ECG (MECG), breath and EMG interference (signal *slp32*) and the FECG, obtained from an adult's ECG (*slp48*) after a decimation by 2 without sampling rate changes.

Since it is possible to assume a time-invariant mixing also for the real dataset [11], the back-projected FECG sources (pFECGs) estimated with the original batch JADE can be taken as the "gold standard". It is worth to note that a time-variant mixing over some blocks means that a single linear combination of the sources does not exist within those blocks, even if a tracking algorithm such as OL-JADE can still try to provide a possible solution avoiding permutations of the estimated sources.

For the artificial dataset, the exact pFECGs are shown in Fig. 1 whereas those estimated with OL-JADE are presented in Fig. 2. Abrupt variations in the amplitude of the pFECGs within the same trace, for all the traces, are clearly visible in Fig. 2. They cannot be imputed neither to time variances (absent) nor to the approximated whitening inversion, as we can easily show. A direct estimate of the error related to such processing is not possible because we are inverting the whole process for the FECG sources only.

We already argued [11] that some separation errors are caused by a poor statistical information on the noise sources due to the limited sliding window size of OL-JADE. Therefore, amplitude fluctuations in Fig. 2 are caused by the emphasis of the separation errors for a weak source due to the back-projection that exploits imperfect estimates of $\mathbf{W}$ and $\mathbf{R}$. This is confirmed enlarging the window size of OL-JADE to 4096 samples/channel. The pFECGs are shown in Fig. 3 where, with the same whitening inversion, the amplitude fluctuations are less intense. Moreover, a comparison with a block-by-block application of the batch JADE algorithm with the same sliding window

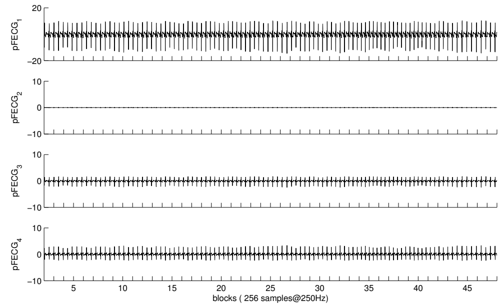

Figure 1. Exact pFECGs for the artificial mixtures.

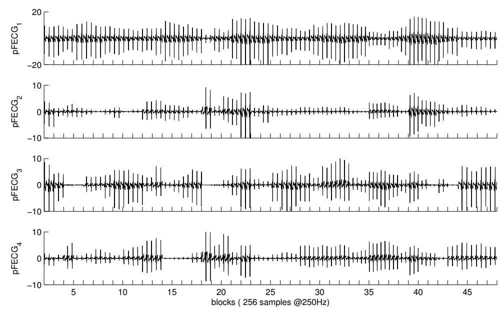

Figure 2. OL-JADE pFECGs for the artificial mixtures.

size of OL-JADE (hereafter called BB-JADE [11]), where the whitening matrix can be exactly inverted, reveals in Fig. 4 a behavior similar to the OL-JADE one. A comparison in terms of *rms* error (Fig. 5) allows to conclude that:

- the pFECGs achieved exactly inverting the batch JADE present the lowest error;
- the pFECGs achieved inverting OL-JADE with extended window size show a reduction in the *rms* error everywhere but the first blocks where the sample-by-sample whitening undergoes stabilization processes;
- the pFECGs achieved inverting BB-JADE are affected by an error which is similar (but lower) to that achievable with OL-JADE.

The differences between OL-JADE and BB-JADE can be imputed more to the approximated whitening, also influencing the subsequent stage, than to the LS inversion process, which numerically we found to be quite precise on artificial signals.

The pFECGs estimated by OL-JADE on the real dataset (Fig. 6) exhibit variations in their amplitude as for the synthetic database, for all the traces, in the block intervals (1, 14) and (28, 32). Outside such intervals, pFECG amplitudes moderately oscillate in a reasonable range. Figure 7, shows the variance of the pFECGs computed block-wise. There can be seen that the 3 pFECGs corresponding to the thoracic leads always present the lowest power among the

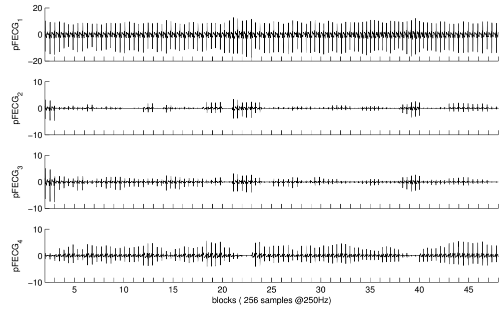

Figure 3. OL-JADE pFECGs when using 4096 samples/channel.

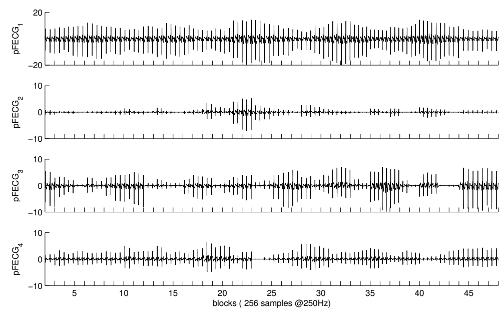

Figure 4. BB-JADE pFECGs for the artificial mixtures.

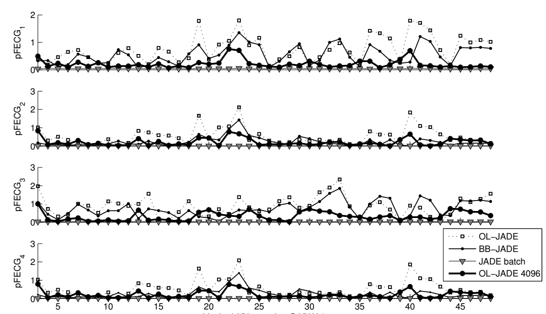

Figure 5. pFECGs *rms* error for the artificial dataset.

traces, excluding the initial fluctuations in OL-JADE due to the recursive whitening stabilization. The better behavior shown by the OL-JADE version with enlarged window size confirms that power estimation errors vanish in the intervals where the OL-JADE errors were referable to a poor statistical information on the noise sources.

The back projection algorithm, coded and optimized in C, has been profiled on a TMS320C6713 floating point DSP, requiring about 2.6M cycles/block. Since the overall memory occupation exceeds the limits of the DSP internal memory, without memory optimizations the whole OL-JADE with back-projection now requires about 140M

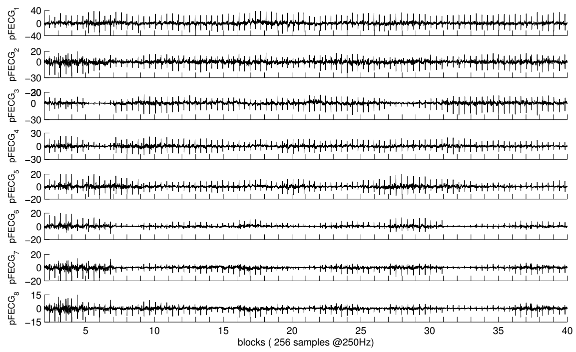

Figure 6. OL-JADE pFECGs for the real database.

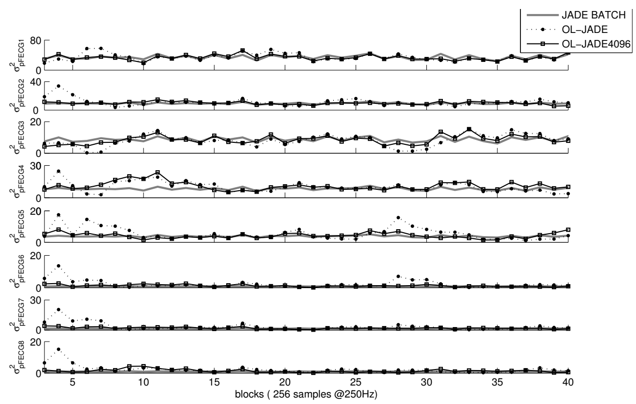

Figure 7. pFECGs variances for the real database.

cycles/block, which is largely within the real-time bound of 307M cycles imposed by the application when running on the chosen platform at 300MHz.

4. Discussion and conclusions

In this paper we proposed an LS approximation of the inversion of the OL-JADE separation process, in order to estimate the average power contribution of the FECG sources at the electrodes. Such back-projection can be exploited to guide a blind electrodes positioning on the mother's body aimed at the maximization of the SNR, being able to run in real-time on a DSP along with the OL-JADE algorithm.

The inversion approach showed to be reliable in providing an acceptable power ranking. A special care must be taken in order to avoid both the first seconds of registration (due to stabilization of the recursive whitening) and the intervals when the real-time separation experiences troubles clearly identifiable in the estimated sources. Due to the amplitude fluctuations in the back-projected sources, it is also worth to avoid trusting the power ranking instantaneously, rather preferring to look at an average trend.

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