Sensor Array and Electrode Selection for Non-invasive Fetal Electrocardiogram Extraction by Independent Component Analysis

Frédéric Vrins[1], Christian Jutten[2], and Michel Verleysen[1]

[1] Université catholique de Louvain, Machine Learning Group
Place du Levant, 3, 1380 Louvain-la-Neuve, Belgium
{vrins,verleysen}@dice.ucl.ac.be
[2] Institut National Polytechnique de Grenoble, Images and Signals Laboratory,
Avenue Félix Viallet 46, 38031 Grenoble, France
jutten@lis.inpg.fr

Abstract. Recently, non-invasive techniques to measure the fetal electrocardiogram (FECG) signal have given very promising results. However, the important question of the number and the location of the external sensors has been often discarded. In this paper, an electrode-array approach is proposed; it is combined with a sensor selection algorithm using a mutual information criterion. The sensor selection algorithm is run in parallel to an independent component analysis of the selected signals. The aim of this method is to make a real time extraction of the FECG possible. The results are shown on simulated biomedical signals.

1 Introduction

In order to improve the accuracy of their diagnosis, detect the fetal distress and avoid unnecessary caeserian deliveries, the obstetricians are interested in completing the information given by the fetal heart rate variability (FHRV) by a waveform analysis of the fetal electrocardiogram (FECG) signal. Moreover, FECG could be a very efficient way for *in utero* fetal heart monitoring and pathology detection during the pregnancy.

Today, this signal can be catched during the labour through a sensor located on the scalp of the fetus, and its diagnostic reliability is confirmed. Obviously, this method can only be applied when the fetal membranes are broken, *i.e.* during the delivery.

To make earlier FECG-based fetal monitoring possible, it can be interesting to develop a non-invasive method to extract this signal. In addition to the possibility of an earlier analysis, a non-invasive method to measure the FECG signal has other advantages. For instance, such method is less stressful for the fetus, because there is no contact between its body and the measurement instrumentation. Furthermore, as the sensors are located on the pregnant woman's abdomen, sanitary precautions are less crucial.

Recently, some authors have shown that this problem can fit into the blind source separation (BSS) framework, where the 'mixtures' are the signals recorded

C.G. Puntonet and A. Prieto (Eds.): ICA 2004, LNCS 3195, pp. 1017–1024, 2004.

by external sensors, and the original sources are signals emitted by maternal and fetal muscles. Previous works based on this method for the FECG extraction have given promising results [1–3]. In practice, even if the results of the extraction are satisfactory, some assumptions on the model can be slightly violated (e.g. linearity and instantaneity of the mixture), and the location and the number N of the external sensors $\mathcal{S} = \{S_1, \ldots, S_N\}$ (recording signals $\mathcal{X} = \{X_1, \ldots, X_N\}$ respectively) is a question still under debate.

In this paper, a hundred-electrodes belt (N=100) [4], located around the pregnant woman's abdomen, is used. In order to be able to extract m sources in real-time, a subset $\mathcal{X}^\star$ of $n < N$ signals $X_i^\star$ recorded by *selected sensors* ($S_i^\star$, respectively with $1 \leq i \leq n$) will be processed by a BSS algorithm (discarding all other electrodes). It will be shown that choosing an appropriate criterion for the selection of the n signals gives interesting results: the extraction can be performed on few sensor signals. Furthermore, it seems that in some cases, an optimal number $n \geq m$ of selected signals appears: the quality of the FECG extraction – possibly after projection by principal component analysis (PCA) – using only $\mathcal{X}^\star$ is improved by comparison to the performances reached if the whole set $\mathcal{X}$ of signals is used in the extraction process ($n = 100$).

In the following of this paper, we will first stress the importance of the FECG signal for the obstetricians. In the next section, we will discuss on a non-invasive (parallel) process to extract this signal. In section 3, the sensor selection algorithm, based on the mutual information, is detailed. Finally, simulation results are presented, before concluding.

2 FECG Measurement Process

2.1 Non-invasive Measurement

A non-invasive method to extract the FECG signal seems thus very attractive. Unfortunately, sensor signals record mixtures of electrical components, due to the electrical activity of several physical sources: the fetal and maternal hearts, the diaphragm and the uterus, among others. The fetal contributions (due to the fetal heart muscular activity) are minor by comparison with these electrical sources, and classical signal processing (like de-noising, filtering, ...) does not allow us to recover the FECG.

One of the most recently investigated methods in order to recover the FECG is BSS. Indeed, the sensor signals actually record a mixture of the electrical signals emitted by the original sources. If the sources are mutually independent and if their mixture is linear, instantaneous and noise-free (or of negligible power), the well-known method of independent component analysis (ICA) is able to recover the original sources, up to a scale factor and permutation [1–3]. In the FECG case, these indeterminations do not matter, because the analysis focuses only on waveforms. Note that the identification of the FECG signal among all the estimated sources signals is a quite easy task, but extracting a complete PQRST complex requires much more effort, especially due to the residual noise.

2.2 Optimal Number and Location of External Sensors

In non-invasive methods, the sensors must be obviously external. In the ideal case of source separation (linear, instantaneous and noise-free mixtures of independent sources), a necessary condition to perfectly recover the original sources is that the number of external sensors must be greater or equal to the number of original sources. As a consequence, the location of sensors does not seem important. Nevertheless, an additional condition exists on the sensors: they must record 'different mixtures'. Indeed, if the number of sensors is equal to the number of sources but two sensors record exactly the same signal, the system is overcomplete and the inversion of the mixing system becomes impossible (null determinant). Similarly, all sources must be involved in the recordings with a non-zero variance. These considerations and the very low power of the FECG signal (by comparison to the electrical environment) explain why the location of the electrodes is an important problem. It is reasonable to think that relevant locations of the electrodes can improve the extraction of the FECG signal, while others can deteriorate it [5]. Moreover, as the fetus moves, it is clear that it does not exist an optimal location for the sensors, constant in time. Furthermore, some electrodes may record irrelevant signals (for example because of a poor contact between the mother's skin and the sensor itself). For all these reasons, it seems to be careful to place a lot of electrodes on the mother's body, possibly further discarding some of them by some selection algorithm.

2.3 Fetal ECG Extraction

The previous discussion justifies the sensor-array approach for the FECG application. In this section, a belt of hundred electrodes (located around the abdomen of the mother) is first presented. Next, the processing of the signals recorded by these sensors (in order to allow a real-time extraction of the FECG) is briefly explained.

A Hundred Electrodes Belt. Consider an array of ten rows and ten columns[1] of electrodes [4], located around the pregnant woman's abdomen (each row i and column j are labelled from 1 to 10). The sensor located at the intersection of the i^{th} row and j^{th} column is noted S_{ID}, with $ID(i,j) = (i-1) \times 10 + j$. The associated recorded signal is X_{ID}.

Parallel Processing. Recall that most of the ICA algorithms separate up to as many sources as sensors. If the number of sources is lower than the number of electrodes, convergence problems (switching problems due to the permutation indeterminacy) may appear. In order to avoid this problem, a dimension reduction by PCA is usually first applied. Nevertheless the projection of the

[1] Of course, other grid geometry of electrodes can be proposed.

100-dimensional data[2] on the subspace of the original sources ($m << 100$) requires the eigenvalue decomposition of the mixture covariance matrix, which can be critical from a computational complexity point of view. In order to allow a real-time extraction, the discarding of some electrodes must be investigated: this will also reduce the computation time of the FECG separation.

The first parallel processing is the electrode selection algorithm. It consists in selecting/discarding several electrodes from the initial set $\mathcal{S} = \{S_1, \ldots, S_{100}\}$ in order to select 'interesting' sensors to reduce the computational time of the extraction process, keeping satisfactory performances of the FECG recovery. Only a subset of $n < 100$ electrodes ($\mathcal{S}^\star = \{S_1^\star, \ldots, S_n^\star\}$) will be analyzed by the source extraction algorithm. The duration of the selection algorithm may be greater than the separation process. An ICA algorithm will then process the signals recorded by the selected sensors $S_i^\star$'s, possibly after PCA if $n > m$. The selection algorithm is run continuously in parallel to the separation one, to select new sets of n electrodes. After each new subset $\mathcal{S}^\star$ is built, the PCA/ICA is run on $\mathcal{S}^\star$, in order to process *in real-time* the associated signals; then the selection algorithm is restarted (with $\mathcal{S} = \{S_1, \ldots, S_{100}\}$).

3 Sensor Selection Algorithm

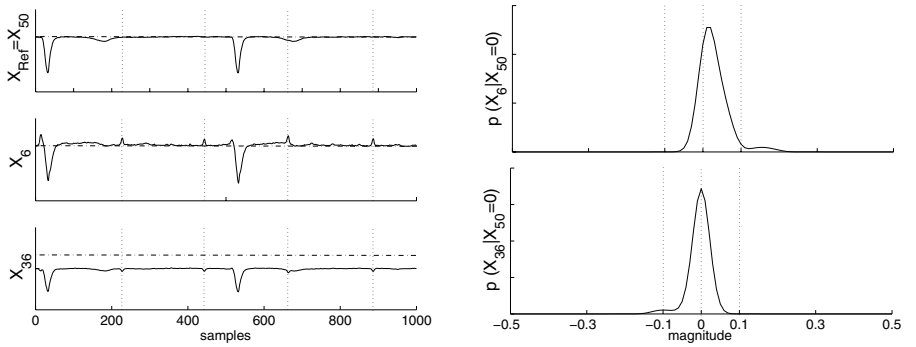
In this section, an unsupervised criterion for the selection of electrodes is presented. Its interpretation is emphasized in the context of the FECG extraction.

3.1 An Information-Based Criterion

In order to extract correctly the FECG signal even with a low number of sensors, it seems natural to look for signals that drive different electrical components due to the fetal heart's activity. Note that such task may not be accomplished by a classical spectral analysis, because in pathological cases, the frequencies of the maternal and fetal hearts may be very close. By contrast, the probability density functions (pdf) of the sensor signals may contain interesting information. The pdf are estimated here by the Parzen estimator with isotropic Gaussian kernels of standard deviation equal to 0.02 (see [6] for more details)

Consider a signal X_{Ref} (which will be called in the following the 'reference'), which is the closest one from the pure maternal ECG signal ($X_{Ref} \simeq$ MECG). In the simulations below, X_{Ref} is recorded by sensor S_{50}. By contrast to this signal, the temporal structure of other ones may contain electrical components due to the muscular activity of the fetal myocardium. One can observe on Fig. 1(a) that when X_{Ref} takes values equal to zero (horizontal dashed line), X_i (with $i = \{6, 36\}$) can take values different from zero due to i) the centered noise on X_i and ii) the fetal R-waves (located on the vertical dotted lines). These

[2] Using one electrode as a reference, a 100-electrode array provides 99 signals, which are the voltage difference between the reference and the 99 remaining electrodes. Changing the reference electrode can provide up to $100 \times 99/2 = 4950$ different signals.



(a) Temporal (normalized) structure of three recorded signals.

(b) Conditional density functions of X_6 and X_{36} w.r.t. $X_{Ref} = 0$.

Fig. 1. Temporal and (conditional) statistical structure of three recorded signals.

considerations explain why the conditional density (cpdf) $p(X_i|X_{Ref} = 0)$ does not reduce to a symmetric Gaussian (because of the kernel estimator) function (see Fig. 1(b)); symmetric result would be obtained for $p(X_j|X_{Ref} = 0)$ if the difference between X_j and X_{Ref} was only due to symmetric effects (a.o. noise). The R-wave is approximatively triangular (i.e. with uniform distribution) and is not centered, contrarily to the noise. Consequently, the asymmetry of the cpdf $p(X_i|X_{Ref} = 0)$ is mainly due to the fetal R-waves: it is thus an interesting way to identify signals that drive important fetal contribution.

Nevertheless, a simple measure of the cpdf asymmetry is not robust. Indeed, this function corresponds (up to a scale factor ensuring a unitary area) to a particular 'slice' ($X_{Ref} = 0$) of the joint pdf between the reference and the recorded signals. This slice becomes irrelevant if an offset appears on X_{Ref}. In order to circumvent this problem, it is preferable to consider the specificity of the 'shape' of the whole pdf. For this reason, another criterion for selection is preferred, based on the mutual information (MI), noted I (see [7]). Of course, the aim of the preprocessing detailed in the previous section is to reduce the number of electrodes to be processed by the separation algorithm; its role is thus mainly to reduce the dimensionality of the 'effective' inputs. The first selected electrode is S_{Ref}. In the algorithm (detailed in Fig. 2), while $k < n$, the sensor $S_k^\star \doteq S_i$ ($S_i \in \mathcal{S}$) is selected if X_i minimizes the sum of the MI's with the previously selected signals (line 6 in Fig. 2). Next, this sensor is removed from $\mathcal{S}$.

3.2 Interpretation of the SenSelec Algorithm

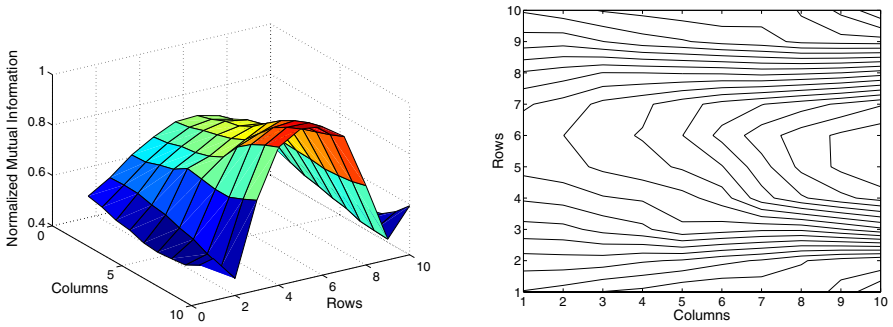
According to the meaning of I (see [7]), the selected signals will be quite independent (because of the minimization of a MI-based criterion). Therefore, the SenSelec algorithm constitutes a good preprocessing for ICA (that consists in finding the rotation of signals that rends them as independent as possible). It must be stressed that in the case of the FECG extraction, the selection of the

SenSelec $(\mathcal{S}, Ref, n)$

$S_1^\star \leftarrow S_{Ref}$ // *reference electrode*
$\mathcal{S} \leftarrow \mathcal{S}/\{S_{Ref}\}$
$\mathcal{S}^\star \leftarrow \{S_1^\star\}$
for $k \leftarrow 2$ **to** n **do**
  for $i \leftarrow 1$ **to** $100 - (k-1)$ **do**
    $\mathcal{C}(i) \leftarrow \sum_{j=1}^{k-1} I(X_j^\star, X_i | S_i \in \mathcal{S})$ // *cost function*
  $j \leftarrow argmin_i(\mathcal{C})$ // *ID of winner sensor*
  $S_k^\star \leftarrow S_j$ // *winner sensor*
  $\mathcal{S} \leftarrow \mathcal{S}/\{S_j\}$ // *removing winner sensor*
  $\mathcal{S}^\star \leftarrow \mathcal{S}^\star \bigcup \{S_k^\star\}$ // *update selected subset*
Return $\mathcal{S}^\star$; // *set of selected sensors*

Fig. 2. Electrode selection algorithm. The cost function $\mathcal{C}$ is based on the mutual information between the selected and unselected electrodes.

electrodes is actually done according to the fetal contributions in the signals [6]. For instance, $X_2^\star$ minimizes the MI with $X_{Ref} \simeq$ MECG (i.e. which is the most independent from it); here, $X_2^\star$ drives an important fetal contribution (in the simulations below, $X_2^\star = X_6$, see Fig. 1(a)). The shape of $I(X_i, X_{Ref})$ is given in Fig. 3. We can observe that the 'distance' between X_i and X_{Ref} mainly varies along the columns.

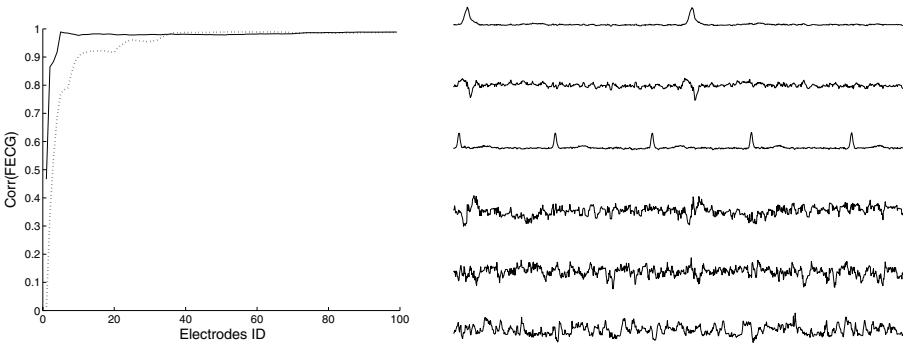


(a) 3D representation (b) Level curves representation

Fig. 3. Mutual information between each recorded signal and the reference vs the location of the sensor.

4 Performances of the Fetal ECG Extraction

In this work, simulated signals have been used. This is useful in order to be able to use correlation-based criterions between the estimated FECG and the true one. The simulator used here is a realistic model of the electrical interaction in the maternal body. It was shown that in such 'real-world' mixtures, it is difficult to find a reliable blind criterion to estimate the quality of the extraction



(a) Correlation between the true and the estimated FECG's *vs* n, using i) SensSelec$(\mathcal{S}, 50, n)$ (solid line) and ii) sets of electrodes taken in numerical order (dotted line).

(b) Separated sources if the six first signals are selected with SensSelec$(\mathcal{S}, 50, 6)$. The optimal extraction of the FECG is reached for $n = n^\star = 6$, third separated signal.

Fig. 4. Extraction performances vs n (left) and separated sources for $n = n^\star$ (right).

of each source, one by one [8]. Furthermore, the hardware instrumentation is quite expensive, and the simulation is a useful step before material realization. The model used to simulate the signals includes both real measurement and simulated data for the sources and the mixing environment. More details about this model can be found in [9]. The selection algorithm is applied here on these simulated sensor signals.

If the number n of selected signals is greater than the – supposed – number m of sources, then the signals are projected by PCA on the sources subspace (m has been taken equal to 6). In order to test the validity of the algorithm, we have plotted in Fig. 4(a) the correlation curve between the original FECG and the estimated one (the extraction was done using the JADE algorithm [10]). We can observe that if we project the six first selected signals, the correlation between the original FECG and the estimated one is even greater than if we had projected directly the hundred signals on the source subspace. This optimal value of n is denoted $n^\star$ (here, $n^\star = 6$). The associated estimated sources are given in Fig. 4(b).

5 Discussion and Conclusion

It was explained why many sensors (say N) should be involved in the measurement process to non-invasively extract the fetal ECG signal. But difficult problems to extract the sources in real-time occur because of this high dimensionality; for example, the computational cost related to the projection can be high. In order to circumvent this problem, a sensor selection method was derived, using an unsupervised criterion based on the mutual information. The first 'selected' signal ($X_1^\star$) must be chosen by other means. The MI criterion was shown to be linked to the fetal content if $X_1^\star$ is close from the pure maternal ECG. The

selection algorithm builds a subset of the original sensors; the associated signals will be processed (possibly after a PCA to guarantee a square mixing system) by a BSS algorithm. Selecting a subset of signals has three major advantages. First, it reduces the computational cost of the extraction process, and allows us to separate the sources in real time. Secondly, if the number of selected electrodes is 'well chosen' ($n = n^\star$), it can be possible to obtain better extraction performances than if all the sensors were involved in the extraction process ($n = N$). In real situations however, the original source is unknown and a 'blind' criterion must be used to measure the 'FECG extraction quality', instead of the correlation; this task may reveal difficult. Note that in practice, taking $n > n^\star$ does not seems to be very thorny from the FECG separation performances point of view. Third, the selection process is able to choose an optimal electrode set, despite the fetal motion.

Further investigations will include extension of the selection process in noisy mixtures, the test on actual FECG data and the determination of $n^\star$.

References

1. De Lathauwer, L., De Moor, B., Vandewalle, J.: Fetal electrocardiogram extraction by blind source subspace separation. IEEE Trans. Biomed. Eng. **47** (2000) 567–572
2. Vigneron, V., Paraschiv-Ionescu, A., Azancot, A., Jutten, C., Sibony, O.: Fetal electrocardiogram extraction based on non-stationary ica and wavelet denoising. In: 7^{th} Symposium on Signal Processing and Appl., Paris, France (2003) 69–72
3. Mareossero, D.E., al.: Independent component analysis for fetal electrocardiogram extraction: A case for the data efficient mermaid algorithm. Neural Networks for Signal Processing (2003, Toulouse, France) 399–408
4. Vigneron, V., Azancot, A., Sibony, O., Herail, C., Jutten, C.: Dispositif materiel et logiciel d'extraction d'ecg foetal. enveloppe Soleau, Institut National de la Protection Industrielle (France) (2002)
5. Vrins, F., Lee, J., Verleysen, M., Vigneron, V., Jutten, C.: Improving independent component analysis performances by variable selection. In: 13th IEEE workshop on Neural Networks for Signal Processing (NNSP 2003), Toulouse (France) (2003) 359–368
6. Vrins, F., Vigneron, V., Jutten, C., Verleysen, M.: On the extraction of the snore acoustic signal by independent component analysis. In: The second IASTED conf. on Biomedical Engineering (BioMED04), Innsbruck (Austria) (2004)
7. Cover, T.M., Thomas, J.A.: Elements of information theory. Wiley and sons (1991)
8. Vrins, F., Archambeau, C., Verleysen, M.: Towards a local separation performances estimator using common ica contrast functions ? In Verleysen, M., ed.: proceedings of ESANN'04, the 12^{th} European Symposium on Artificial Neural Networks, Bruges (Belgium), d-side publications (2004) 211–216
9. Schmidt, M.: Sensor array for fetal ecg signals. simulation, sensor selection and source separation. Master of science, INPG, Laboratoire des Images et des Signaux, Grenoble, France (2003) supervised by V. Vigneron and C. Jutten.
10. Cardoso, J.F.: Source separation using higher order moments. Proceedings of the IEEE, Int. Conf. on Acoustics, Speech and Signal Processing (ICASSP'89) (1989, Glasgow, England) 2109–2112