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Abdominal Electrodes Analysis by Statistical Processing for Fetal Electrocardiogram Extraction

F. Vrins[1], V. Vigneron[2], C. Jutten[2] and M. Verleysen[1]
[1] Microelectronics Laboratory, Machine Learning Group
UCL-DICE Place du Levant 3, 1348 Louvain-la-Neuve, Belgium
[2] Images and signals Laboratory
LIS-INPG Avenue Félix Viallet 46, 38031 Grenoble cedex, France
E-mail: {vrins, verleysen}@dice.ucl.ac.be, {vvigne, jutten}@lis.inpg.fr

Abstract

Obstetricians were asking the engineering support to study more extensively any technical possibility to electronically get some useful information from the whole PQRST complex of the fetal electrocardiogram (fECG) in order to identify eventual sign of fetal distress (FD). The latter should indeed be found as a more reliable information for the clinician with the potential benefit of increasing the sensibility as well as the specificity of the diagnosis of FD. A way to achieve this goal is Blind Source Separation. In this case, the extraction of an estimation of the fetal PQRST complex can be solved using Independent Component Analysis on signals recorded through electrodes located on the pregnant woman abdomen. Today, neither theoretical nor simulation considerations were investigated to determine an optimal number and location of these electrodes, despite possible important consequences on the extraction performances. We propose here a method to identify the location of electrodes (depending of the position of the fetus) that drive electrical components due to the fetus by analyzing the (joint and marginal) density functions of the recorded signals. This result allows to evaluate the 'interesting' sensors, therefore allowing electrode selection when many sensors are involved in the measure. We show several simulation results on artificial signals.

Key Words
Fetal electrocardiogram analysis, non-invasive measurement, mutual information, blind source separation.

1 Introduction

In the everyday clinical practice, the fetal heart rate variability (FHRV) analysis does not render the obstetricians sufficiently able to get an accurate diagnosis of fetal distress (FD). As a consequence, the analysis of this parameter taken alone has led in some cases to unnecessary caesarean deliveries and the clinicians were asking for a more reliable test. The fetal electrocardiogram (fECG) should be of interest in helping them to further evaluate the well-being of the future newborn. In the time being, the PQRST complex (Figure 1) can be catch through an invasive sensor located on the fetal scalp [1]. Of course, this method of measuring the fECG can only be applied during the labour, when the fetal membranes have been broken. Many researchers have tried to respond the clinician's needs. They have developed a non-invasive technique to extract the fECG signal, in order to render it able to analyze the well-being of the fetus during the labour, and even more during the whole pregnancy. Blind Source Separation (BSS) is one of the methods that were recently investigated [2, 3, 4] to measure the fECG by a non-invasive manner. It consists in the extraction of original independent sources from mixtures of them. In this application, the sources are the fECG and maternal electrocardiogram (mECG), diaphragm and uterus and the mixtures are recorded through electrodes located on the pregnant woman abdomen (potentials measured on the mother's skin are the sum of electrical fields). BSS can be achieved by Independent Component Analysis (ICA), under mild assumptions.

The problem of an optimal placement of the electrodes is important, because it can really influence the quality of the extracted signal [3]. Similarly, the number of sensors to be used is not known. We propose here to analyze signals recorded by a 10-by-10 grid of electrodes (100 sensors) placed around the pregnant woman's abdomen ([5], see Figure 2). We emphasize the difficulty of a frequency-domain analysis; we show that an analysis based on marginal and joint densities of the recorded signals allows to identify the ones that have fetal components. In [3], a density-based criterion was applied to select electrodes in order to improve the performances of the separation algorithm.

This paper is organized as follows: in the next section, we discuss the method commonly used to diagnose the well-being of a fetus. BSS is briefly introduced in section 3. In section 4, artificial ECG signals are presented, together with a map of the electrodes on the grid. Sections 5 and 6 present the frequency and density specificities of the signals. In sections 7 and 8, we introduce intuitive criterions to identify interesting electrodes, and in particular the mutual information concept. In section 9, we emphasize that a variable selection algorithm inspired from mu-

tual information leads to select signals from the grid which drive effectively an important fetal contribution.

2 Diagnosis of the fetal well-being

In this section, we emphasize the interest of recording the whole fECG complex, in order to improve the quality of the fetal surveillance in comparison with the classical method of the FHRV analysis.

2.1 Fetal Heart Rate Variability

Until few years, it was thought that a monitoring laid on the FHRV allowed to identify every fetus suffering from FD. This method - also called the cardiotocographic approach (CTG) - was however unable to bring up in some clinical circumstances both sufficient and acceptable sensibility and specificity leading to an unacceptable increase of cesarean deliveries which could have been avoidable. It explains that despite of 30 years of clinical experience, the absolute benefits which can be got from the CTG surveillance is still under debate. An alternative to the sole use of the FHRV analysis could be found by the combination of the latter with the waveform analysis of the fECG.

2.2 The PQRST complex of the ECG signal

The PQRST complex (see Figure 1) is an electric signal produced by the contraction of the heart's muscle called *myocardium*. It is composed of three parts:

- the P-wave reflects the contraction of the auricles;
- the QRS-complex is associated with the contraction of the ventricles. Due to the magnitude of the R-wave, it is extremely reliable;
- the T-wave, which corresponds to the repolarisation phase which follows each heart contraction.

The delay associated to the R-R interval leads to the heartbeats frequency.

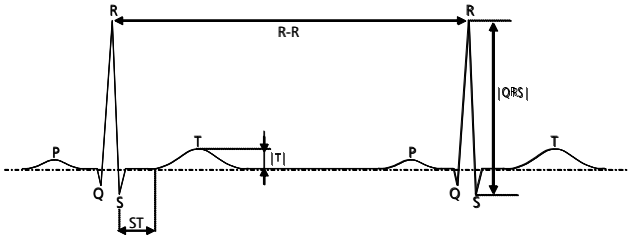

Figure 1. Temporal structure of an ECG (about 2 sec for a sain fetus): the PQRST complex.

2.3 ST analysis

Many technical reports on the ST-segment morphology (translating the fetal myocardium activity) and on the $\frac{|T|}{|QRS|}$ ratio of the fetal ECG (see Figure 1) confirm its diagnostic reliability. However, this method has a drawback in regards with the FHRV analysis : it requires the capture of the ECG complex, and not only a measure of instantaneous frequency. Today, as already mentioned in the introduction, this signal can be catched during the labour through a sensor located on the scalp of the fetus (after the breaking of the fetal membranes). Physicians are interested to have this signal even before the labour, requiring a non-invasive measurement, which can be achieved by Blind Source Separation.

3 ICA and Blind Source Separation

Independent Component Analysis (ICA) consists in *blindly* recovering statistically independent sources ($\mathbf{s} = [s_1, \ \ldots, s_m]^T$) from linear and instantaneous mixtures of them ($\mathbf{x} = [x_1, \ldots, x_m]^T$), which could be translate in matrix formalism as:

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

Under this hypothesis, ICA can thus solve the Blind Source Separation (BSS) problem (see *e.g.* [6, 7]). This requires to find an inverting matrix $\mathbf{W}$ such that $\hat{\mathbf{s}} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{A}\mathbf{s}$, with $\mathbf{W}\mathbf{A}$ equal to the identity matrix, up to a permutation and a diagonal-scale matrix. Each estimated source is thus close from an original one ($\hat{s}_j = \alpha_i s_i$), and a whitening of the observed signals implies $\sigma^2_{\hat{s}_j} = 1$, with $1 \leqslant i, j \leqslant m$. By definition, the statistical independence between the sources implies that the product of the marginal densities (PDF) p_{s_i} equals the joint density (JPDF) p:

$$\prod_{i=1}^{m} p_{s_i}(s_i) = p(\mathbf{s}) \ . \tag{2}$$

In the extraction of the fECG signal, the observed signals are recorded by sensors located on the abdomen of the pregnant woman. Next, fECG is extracted by an ICA algorithm (see *a.o.* [8, 9]).

4 Artificial fECG signals

The signals of the electrodes (temporal structure of three of them are given in Figure 3) are the combinations of the electrical fields generated by several independent simulated sources: the maternal heart, the fetal heart, the uterus and the diaphragm. For each of these components, equations of an electrical model are derived.

The shape of the maternal abdomen is considered to be formed by a parabolic function surrounding a middle axis. The difficulty of the task is that an accurate model of the heart is needed because the model has to provide

the orientation of the heart dipole. This is achieved by using a template ECG data file recorded at a sampling rate of 500 Hz (the heart rate is 70 beats/mn). The signal was resampled so that a fetal heart rate was built at about twice the maternal one. Similar manipulations follow for the uterus and the diaphragm. The bioelectrical properties of the uterus are derived from [10]. The bioelectrical model of the diaphragm consists of 6 dipoles, symmetrically located over the uterus. The exact position as well as the amplitude can change over time. The resulting (from superimposition of fECG, mECG, uterus and diaphragm signals) electrical field at the surface allows to simulate signals observed on electrodes according to their locations (see Figure 2).

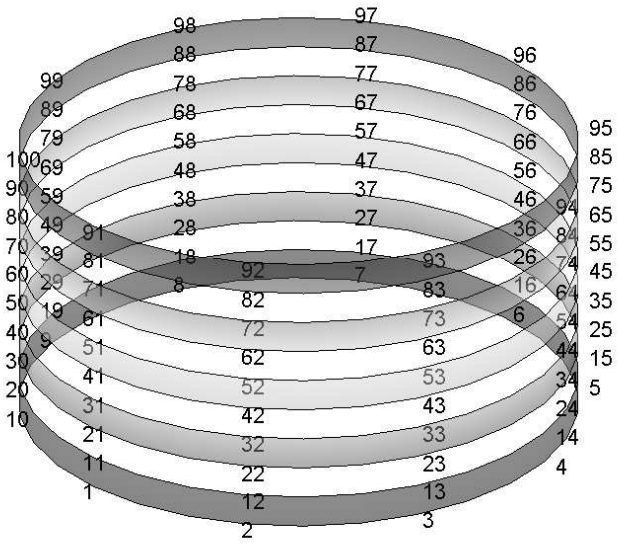

Figure 2. 3D representation of a 100 electrodes grid: location and labelling of the sensors.

Figure 3 shows three recorded signals on sensors 50, 6 and 36 (see Figure 2 for electrodes labelling). The first one catches approximately the pure PQRST complex of the mother, the two others catch components due to the fetal heartbeats.

5 Frequency specificities of recorded signals

As explained in the introduction, one can be interested in detecting signals that have a fetal contribution. The first idea is to analyze signals in the frequency domain, by a Fourier transform (Figure 4).

In general, the frequency of the fetal heartbeats (fHB) is quite close to twice the frequency of the mother's one (fHM): $\frac{fHB}{fHM} \simeq 2$. This ratio can decrease in pathological cases until values very close to one. Unfortunately, in this case, the corresponding patterns in the signal power

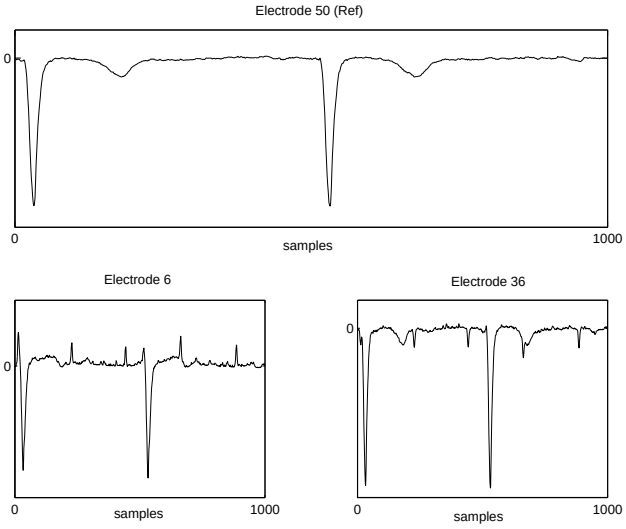

Figure 3. Mixed artificial signals. First row: reference signal, recorded by sensor 50 (mECG PQRST complex); Second row: signals 6 and 36 (compressed in width for a better fetal component visibility).

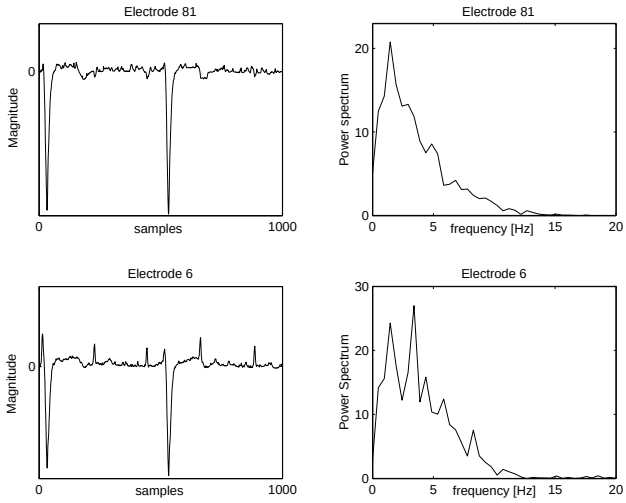

Figure 4. Left: two 'recorded' signals (sensors 81 and 6); Right: their power spectrum, computed by the FFT.

spectrum are very close, so that no really interesting information about the fetal contribution can be extracted from a frequency analysis.

6 Density specificities of the recorded signals

The analysis of probability density functions (PDF) can circumvent the problem encountered in the frequency domain. Indeed, the analysis of the joint PDF (JPDF) between signals and a reference can give interesting information. Consider the joint densities between a reference Ref and electrode signals. The reference is chosen here as the closest

signal from the pure mECG, which is easy to find by external means. The left column of Figure 5 shows respectively the JPDF of Ref with itself (top), and then the JPDF between Ref and electrode 6 (middle) and electrode 36 (bottom) (the right column shows zooms around the origin, the latter being indicated by the intersection of the dotted x and y axes).

The information of a fetal component in signals can be checked by analyzing the conditional densities (CPDF) $p(X|Y=0)$ of the JPDF. Indeed, while the reference signal ($Y = Ref$) takes values around zero, the other one could take values different from zero, due to the fetal R-wave. The presence of the asymmetry of $p(X|Y=0)$ points out a fetal contribution in the X signal. Note that the large 'ellipse' visible on the left figure in the second row indicates a slight phase shift between the mother's R-waves in both signals, contrarily to the graph in the third row. The only case where this analysis may fail is when both the phases **and** the frequencies of the mother and the fetus signals are synchronized.

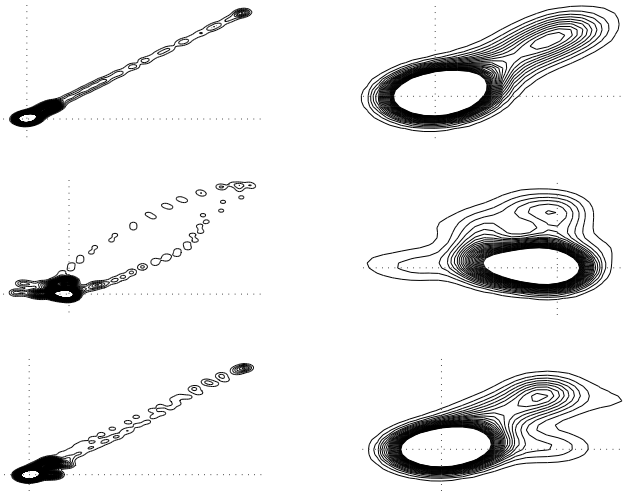

Figure 5. Left: joint density functions $p(X,Y)$ of 'recorded' signals, with $Y = Ref$ being the signal coming from sensor 50 (*pure* mECG).; Right: zooms around the origin. First row: $p(Ref, Ref)$, second row: $p(6, Ref)$, third row: $p(36, Ref)$. Dotted lines indicate the x and y axes. Fetal contribution are visible on the two last rows: the conditional densities $p(X|Y=0)$ are highly asymmetric (see text). For clarity, the sign of signals is inverted to show the JPDF in the first quadrant, and level curves are shown in a limited range.

7 From conditional pdf disymetries to mutual information

In the previous section, we shown that the asymmetry of the CPDF $p(X|Y=0)$ contains relevant information about the fetal contribution in signals. Several criterions could be derived in order to measure this disymetry. One of those could be the following: fold up both parts of the PDF ($X = 0$ being the folding axe), subtract them and measure this difference. However, this measure has drawbacks, in particular the problem of the offset between X and Y. Actually, a measure of deviation between two PDF f and q could be a very convenient criterion. One of those measures is the Kullback-Leibler divergence (KLd)[1]:

$$KL(f,q) = \int f(x) log \frac{f(x)}{q(x)} dx \ . \tag{3}$$

In this application, f could be chosen as the reference, and q the PDF of other electrodes. Another way to measure the deviation between PDF is to measure their (in)dependence. This time, we compute the mutual information [11] I between a specific signal (X) and Ref (Y), which is actually the KLd between the joint density of X and Y and the product of their marginal densities:

$$I(X,Y) = \int p(x,y) log \frac{p(x,y)}{p_X(x) p_Y(y)} dxdy \ . \tag{4}$$

Note that $I(X,Y) \geqslant 0$ with equality if and only if X and Y are independent (see eq. 2). If the joint density is quite far from the product of the marginal densities, one can suppose that the signals are also 'quite different' from an information theory point of view (*i.e.* 'quite independent'). Indeed, a signal with high fetal component must be 'quite different' from the pure mECG signal (recall that Ref is taken as the pure mECG signal).

8 Sensors classification using mutual information

In order to identify electrodes with high fetal contributions, we propose to compute the *normalized* mutual information of each electrodes with respect to Ref : $NI(X) = I(X, Ref)/I(Ref, Ref)$. In practice, the PDF's p_X, p_Y and JPDF p are unknown and were estimated in this case with a Parzen estimator [12] with Gaussian kernels[2].

The method consists - to estimate a one-dimensional PDF - of a sum of T basis kernels $\Phi_t(\mu, \sigma^2, \eta)$ (T being the number of samples of X), centered on $\mu = X(t)$ in the magnitude space (σ^2 is the variance of the kernels, which must be chosen a priori):

$$\Phi_t(\eta, \mu, \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(\eta-\mu)^2}{2\sigma^2}} \tag{5}$$

Then, the estimation $\hat{p}_X$ equals:

$$\hat{p}_X(\eta) = \frac{1}{T} \sum_{i=1}^{T} \Phi_i(\eta, X(i), \sigma^2) \tag{6}$$

[1] Note that by convention : $0 \log 0 = 0$.

[2] Other kernels can be used.

A similar method was derived for the estimation of the JPDF p. The variance σ^2 of the kernels must be chosen large enough to avoid overfitting, but small enough to be sufficiently accurate, in order to achieve $\hat{p}_X \simeq p_X$ and $\hat{p} \simeq p$. The choice of σ^2 is thus directly linked to the variance of X and to the number of samples.

Figure 6 shows $NI(x_i)$ for different values of σ^2. The steps in the curves correspond to changes of row (see electrode map in Figure 2), especially in the middle of the grid. The signals which are the most independent from the reference (sensor 50) are located in the bottom and the top of the grid (low NI).

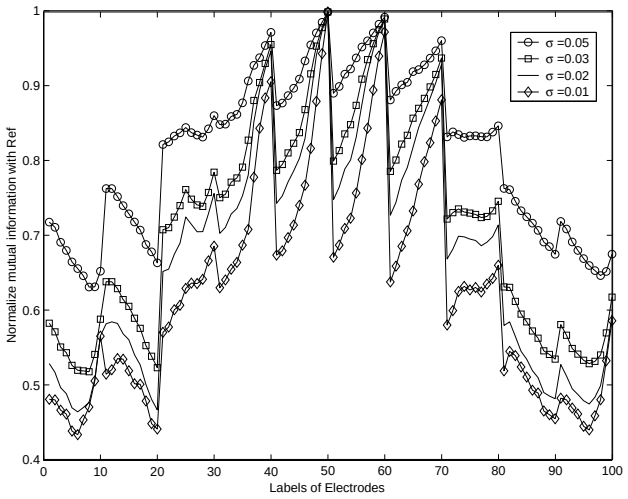

Figure 6. Normalized mutual information between electrode 50 (reference) and each electrode for several values of the smoothing parameter σ^2.

The relevance of NI as a measure of the fetal contribution can be proved on a very simple classification rule. Four well-chosen thresholds on the NI (see Figure 7, where σ has been fixed to 0.02) allows to classify the electrodes in four classes. The means of the signals in each class (Figure 8) show that the fetal contribution is different for each class. This demonstrates that the mutual information between the pure mECG signal and x_i content effectively the information about the fetal contributions in the recorded signals x_i.

Some very simple electrode selection algorithms could be derived from this threshold method, but they present several drawbacks: the choice of the number of class, the numerical values of the thresholds, etc.

9 Electrodes selection as a preprocessing to ICA

In order to circumvent the drawbacks of a simple threshold classification method, with the number of classes a priori fixed, another algorithm is used to select signals which will be processed by ICA.

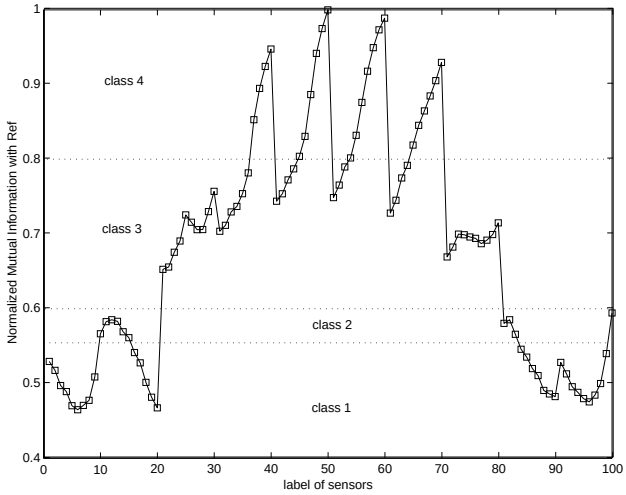

Figure 7. Normalized mutual information between electrode 50 and each electrode ($\sigma = 0.02$). Classification thresholds are indicated by dotted lines.

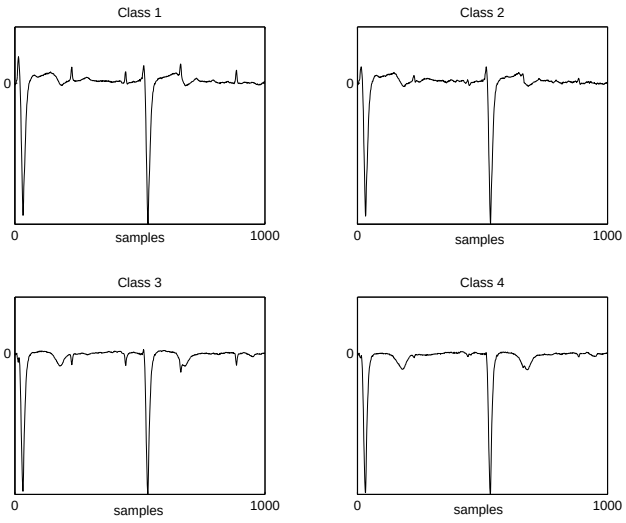

Figure 8. Means of signals in each class.

In [3], an electrode selection algorithm is developed for this application (the (J)PDF's were estimated as explained in section 8). Briefly, the algorithm select m' signals among a set of m mixtures ($x_1, \ldots, x_m$). The first signal $U_1 = Ref$ must be chosen by another means. The z^{th} selected mixture $U_z = x_k$ is the most independent signals (among the $m-(z-1)$ still unselected mixtures) from the $z-1^{th}$ already selected U_j's, *i.e.* the one which minimizes $\sum_{j=1}^{z-1} I(U_j, U_z)$. We stop the algorithm when m' signals are selected ($z = m'$).

Using this algorithm, the three first selected signals (after the reference) were respectively signals from classes 1, 2 and 3. This paper demonstrates that this method select signals with respect to their fetal contributions, as the simple threshold classification. Furthermore, a performance

analysis proves that this algorithm can increase the separation quality, from the Signal-Interference Ratio point of view.

10 Conclusion

The physicians are interested in measuring the whole fetal PQRST signal by a non-invasive manner. Recently, this problem was addressed using Blind Source Separation, where the fetal ECG is one of the desired sources. This problem can be solved with ICA, by the processing of several signals recorded through electrodes located on the pregnant woman's abdomen.

In [3], the authors have shown that a selection of those electrodes can improve the separation because (i) from a computational complexity point-of-view, the number of signals to process by ICA is downsized and (ii) form a correlation or a Signal-Interference Ratio (SIR) point of view, some results have shown that sometimes processing only particular recorded signals among all available ones can improve the separation performances. We have emphasized here that actually, this selection is done with respect to the fetal contribution appearing in the measured signals.

This paper discusses the detection of such contributions. It is shown why, in pathological situations (where the frequencies of fetal heartbeats and mother's ones are similar), a frequency-domain analysis of signals could be irrelevant. We propose a density-based approach, more robust to frequency mismatches. From these densities, we derive a measure of deviation laid on the mutual information between signals.

In this work, we have demonstrated that the evaluation of the mutual informations $I(mECG, x_i)$ between signals x_i and an a priori well-chosen reference (mECG) is able to detect fetal contributions in x_i: classification of signals with respect to their fetal components becomes possible. The electrodes selection algorithm developed in [3] is based on $I(mECG, x_i)$, and gives promising results.

The statistical processing of electrodes (estimation of marginal, conditional or joint density functions and their analysis, mutual information, ...), is thus a powerful tool in order to analyse biomedical signals.

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[3]Obstetrician, High Risk Pregnancy Unit (HRPU), CHC-Site St-Vincent, 4000 Rocourt-Liège-BELGIUM.

[4]Paediatrician-Neonatologist, Neonatal Intensive Care Unit (NICU), CHC-Site St-Vincent, 4000 Rocourt-Liège-BELGIUM.

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