

FETAL ECG ANALYSIS BY REDUCTION OF MUTUAL INFORMATION

Mayurkumar Nanda ,
*Electronics And Telecommunication Department,
 D.J.Sanghvi College Of Engineering, Mumbai
nanda.mayurkumar2@gmail.com*

ABSTARCT:

Fetal electrocardiogram (FECG) signal contains potentially precise information that could assist clinicians in making more appropriate and timely decisions during labor. The ultimate reason for the interest in FECG signal analysis is in clinical diagnosis and biomedical applications. The extraction and detection of the FECG signal from composite abdominal signals with powerful and advance methodologies are becoming very important requirements in fetal monitoring. The signal is a mixture of the fetal ECG, the maternal ECG and noise. The key idea is to project the signal into higher dimensions, and then use an assumption of statistical independence between the components to separate them from the mixtures using Independent Component Analysis

Keywords: Independent Component Analysis; Kullback-Leiber Divergence; .Fetal ecg

1. THE MAIN TEXT

Heart defects are among the most common birth defects and the leading cause of birth defect-related deaths . Every year about one out of 125 babies are born with some form of congenital heart defects . The defect may be so slight that the baby appears healthy for many years after birth, or so severe that its life is in immediate danger. Congenital heart defects originate in early stages of pregnancy when the heart is forming and they can affect any of the parts or functions of the heart. Cardiac anomalies may occur due to a genetic syndrome, inherited disorder, or environmental factors such as infections or drug misuse . However, except for during labor, fetal electrocardiography has not proved an effective tool for imaging specific structural defects. Rather, fetal electrocardiography has been concerned to more global issues such as general ischemia due to specific fetal positioning that chokes the umbilical cord . The reason for this limitation is that the noninvasive fetal electrocardiogram (ECG) is contaminated by fetal brain activity, myographic (muscle) signals (from both the mother and fetus), movement artifacts and multiple layers of different dielectric biological media through which the electrical signals must pass. When continuous electronic fetal heart rate monitoring was introduced into clinical practice in the 1970s, there was enormous optimism that the widespread use of this technology would reduce the incidence of intra-partum fetal injury and death. Unfortunately, fetal heart rate monitoring has not lived up to its initial promise. A meta-analysis of nine randomized, controlled trials comparing fetal monitoring to intermittent auscultation of the fetal heart rate showed that current monitoring techniques increase the use of cesarean, forceps, and vacuum delivery, but do not reduce perinatal morbidity or mortality . Since the advent of fetal heart rate monitoring 40 years ago, there have been no clinically significant advances in intra-partum fetal monitoring. Moreover, continuous fetal monitoring is utilized in over 85% of labor episodes in the United States, and represents the standard of care . Fetal monitoring today is based entirely on the fetal heart rate and does not incorporate characteristics of the fetal ECG (fECG) waveform characteristics that are the cornerstone of cardiac evaluation of both children and adults.

2. PROBLEM DEFINITION

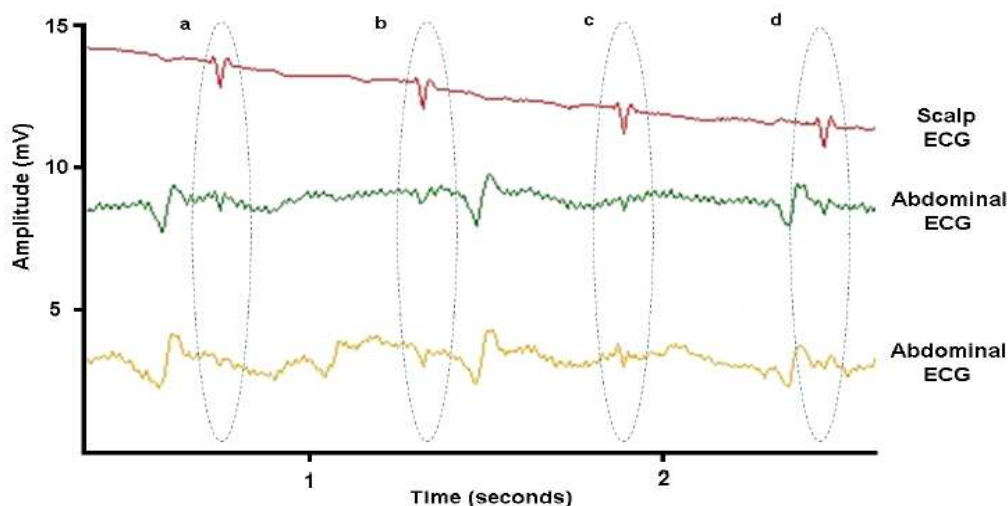


Fig.1 comparison of scalp ECG and Abdominal ECG (Adapted from 3)

Fig.1 illustrates an example of a short segment of fECG recorded both invasively (upper trace) through a fetal scalp electrode, and non-invasively (lower two traces) through electrodes placed on the mother's abdomen. Four fetal beats (labeled a, b, c and d) are circled on all three traces. Note the abdominal traces contain much smaller fetal beats embedded in significant broadband noise, and much larger amplitude artifacts (transient oscillations) which are due to the mother's heart. Note also that the artifacts manifest both in between and on top of fetal heart beats, with a similar morphology to the fetal heart beats.

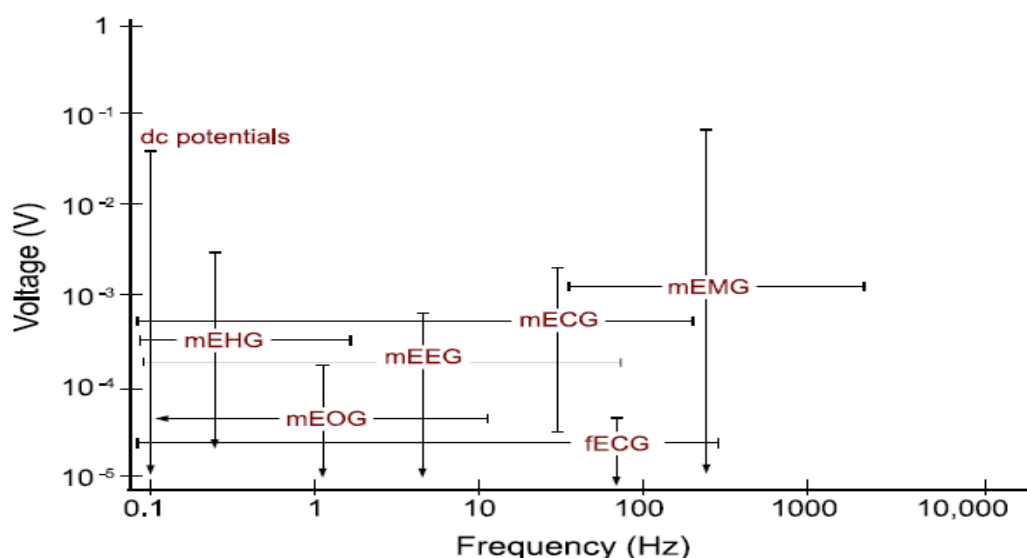


Fig.2 The amplitude and frequency range of different bio-signals, some of which interfere with fetal cardiac signals (Adapted from 3)

In Fig. 2 the amplitude and frequency range of fECG have been compared with other biosignals and artifacts. Accordingly, the fECG is much weaker than the other biosignals. Moreover, from the signal processing

perspective, there is no specific domain (time, space, frequency, or feature) in which the fECG can be totally separated from the interfering signals.

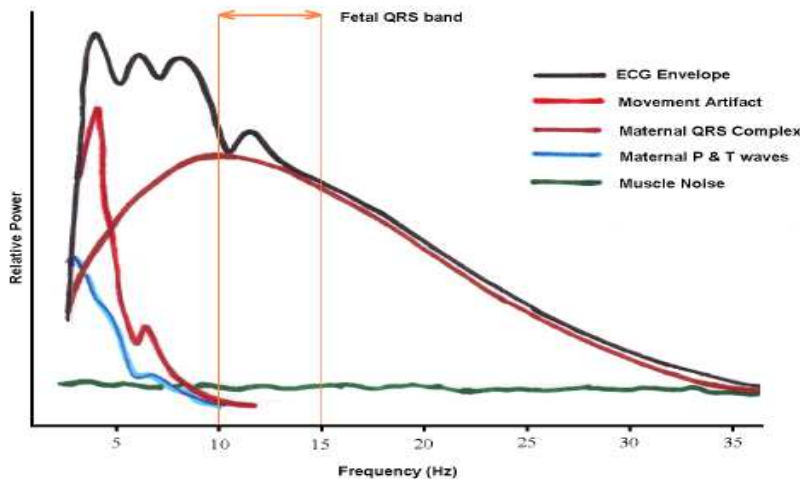


Fig 3 A general representation of the signal, artifacts and noise present in the ECG in the frequency domain (Adapted from 3)

Fig. 3 illustrates the fact that the main part of the fetal heart beat on the electrocardiogram (the QRS complex) lies in the same frequency domain as the adult QRS complex, as well as broadband muscle noise. Despite of the richness of the literature, there are still several key areas that require further study in the field of fetal electrocardiography, particularly in the domain of multichannel noninvasive maternal abdominal measurements.

3. Methodology

In this paper noble technique of Independent component analysis is presented to separate fetal ecg analysis. ICA problem was raised as a cocktail party problem, which demands separating different speaker's voice from each other and background music. In this study, three-channel signals are picked up using three different leads. Each measured signal comprises multiple signal components from different sources. This mixing procedure is depicted in Fig. 4 In this model, the sources $s_1(t)$ and $s_2(t)$ represent signals generated by maternal heart and foetal heart respectively. $s_3(t)$ represents random noise. These signals are transmitted to the maternal body surface through the body issues with unknown parameters a_{ij} , ($i, j=1, 2, 3$). The mixed signals are picked up as $x_1(t)$, $x_2(t)$ and $x_3(t)$ via two abdominal leads and one chest lead respectively using cutaneous electrodes on the maternal body surface. Analytical equations for the ICA model can be expressed in a matrix form as

$$x(t) = As(t) \quad (1)$$

$$\text{where } s(t) = [s_1(t) \ s_2(t) \ s_3(t)]^T$$

$$x(t) = [x_1(t) \ x_2(t) \ x_3(t)]^T$$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

A is called a “mixing matrix”. Superscript T denotes vector or matrix transposition. The goal of ICA is to find a “separating matrix” W , which is as close to A^{-1} as possible, based upon a proper statistical criteria, in order to optimally recover the original source signals as

$$y(t) = Wx(t) = WAs(t) = s(t)$$

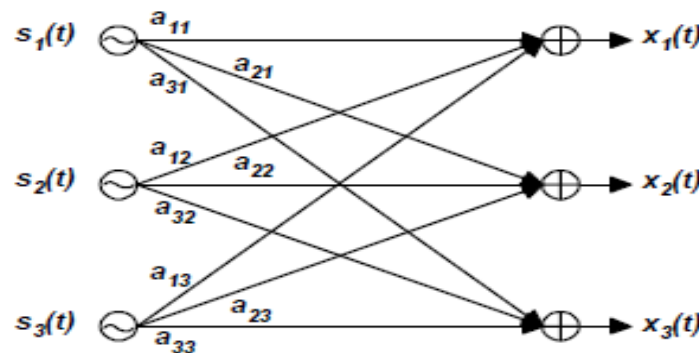


Fig4 simplified mixing of fetus ECG, Maternal ECG and Noise (Adapted from 5)

In a simplified ICA model, we suppose that matrix A is a time invariant (constant) matrix and the propagation delays can be ignored. Signals s_1 , s_2 and s_3 are statistically independent means that their joint probability density function is factorable. The mutual information $I(\mathbf{P}_y)$ is defined as the Kullback-Leibler divergence between the joint density of all signals and the product of their marginal densities as

$$I(\mathbf{P}_y) = \int p_y(\mathbf{u}) \left[\log p_y(\mathbf{u}) - \log \prod_{i=1}^3 p_{y_i}(u_i) \right] d\mathbf{u} \quad (2)$$

It is clear that $I(\mathbf{P}_y)$ will be equal to zero when the recovered signals y_1 , y_2 and y_3 are mutual independent. For an invertible non-linear transformation

$$\mathbf{Y} = g(\mathbf{v}) = g(\mathbf{W}\mathbf{x}), \quad (3)$$

$$p_y(\mathbf{u}) = \frac{p_x(\mathbf{u})}{|(g')^3 \det(\mathbf{W})|} \quad (4)$$

Satisfying above conditions we can apply different algorithms of Independent Component Analysis and extract fetal eeg. Therefore, using observed signals \mathbf{x} and selecting a proper contrast function g , \mathbf{y} can be optimally separated by minimizing $I(\mathbf{p}_y)$ with respect to \mathbf{W} . If the joint probability density function of \mathbf{y} and marginal density functions are known, i.e. a prior knowledge on signal model, maximum likelihood estimation can be applied. If it is not the case, truncating Edgeworth expansion can be used to approximate probability densities. A fixed-point algorithm for updating \mathbf{W} was developed by A. Hyvarinen. Its iterative steps are recapitulated below

1. Choose an arbitrary (random) matrix as an initial \mathbf{W} .

2. Let $W^+ = E\{xg(Wx)\} - E\{g'(Wx)\}W$
3. $W^+ = W^+ / \|W^+\|$
4. If not converged, repeat iteration from step 2.

where $g(Wx)$ is selected as a hyperbolic tangent function, i.e. $g(Wx) = \tanh(Wx)$. The convergence means that the old and new values of W point in the same direction, i.e. their dotproduct is near to one.

4. Simulation Results

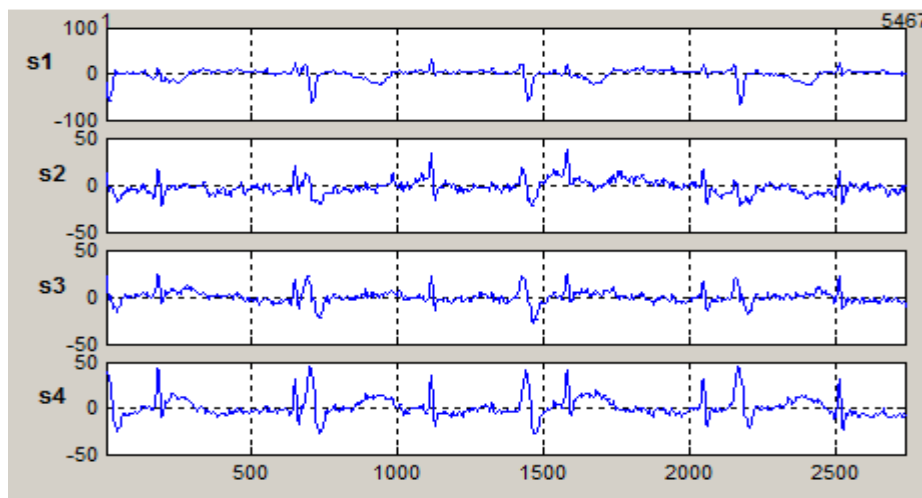


Fig5 Abdomen signals

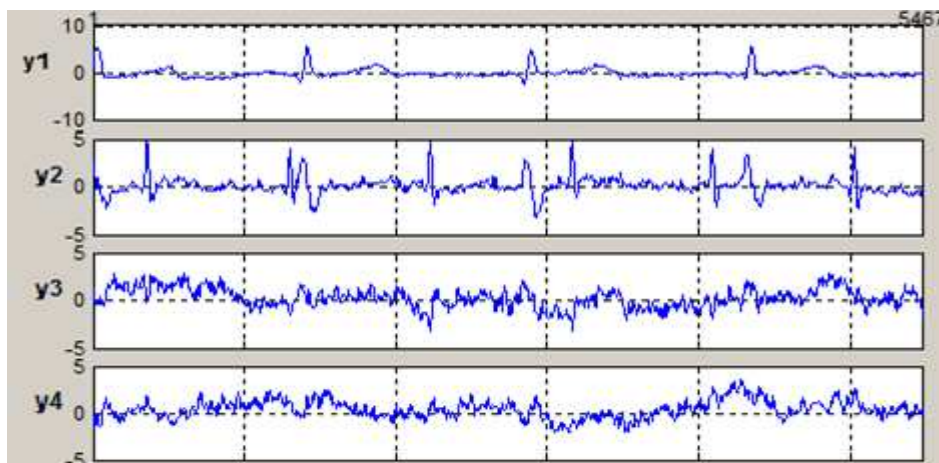


Fig6 Estimated Sources

Fig 5 shows the abdomen signals taken through electrodes from different position of mother abdomen .fig6 indicates separated independent components separated by fixed point ica algorithm. First estimated component indicates fetal eeg. Fixed point algorithm used , uses mutual information as measure of independence rather than non-gaussianity.

5. CONCLUSION

Fixed point algorithm which uses mutual information as measure of independence is used and showed satisfactory results in separating fetal ecg from maternal ecg and other artifacts as compared to other methods using reduction of gaussianity.

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