FOETAL ECG EXTRACTION FROM MATERNAL BODY SURFACE MEASUREMENT USING INDEPENDENT COMPONENT ANALYSIS

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***Abstract* – A method applying independent component analysis (ICA) to detect the electrocardiogram of a prenatal cattle foetus is described. Three channels of signal, one is from chest lead and two are from abdominal leads, are picked up noninvasively by attaching disposable cutaneous electrodes on the body surface of a maternal cow. Measured signals are the mixtures of components including maternal ECG, foetal ECG and random noise. Such mixture procedure is expressed by a time-invariant linear model. To separate foetal ECG from maternal ECG and random noise, the ICA method is applied to find an optimal separating matrix only using measured signals. The optimization uses hyperbolic tangent as a contrast function and minimizes it based upon the principle of mutual information. The method was examined by simulation signals generated by random mixture of two-signal and one-noise sources. Real signals, measured from a pregnant cow having 177-day gestation, are used to verify the separation. The results show that in simulation, both signal and one noise are clearly separated. Real measurement is successfully distinguished into three signal sources, maternal ECG, foetal ECG and random noise. The results suggested the effectiveness of ICA approach in detecting foetal ECG from maternal body surface measurement.**

***Keywords* – Foetal ECG detection, independent component analysis, blind source separation, mutual information**

I. INTRODUCTION

Prenatal diagnosis and monitoring the health status of an unborn cattle foetus is indispensable in preventing natural abortion and premature birth [3]. One of the applicable methods is to measure the foetal electrocardiogram (fECG) and heart rate [4]. However, fECG signal, measured from maternal body surface, is weak and usually contaminated by the maternal electrocardiogram (mECG) and electromyogram (mEMG) as well as random noise. The raw measurement of foetal signal is not enough to detect the foetal heart rate. We present here an approach using only three channels of measured signal to separate fECG from mECG and background random noise.

II. METHOD AND MATERIALS

The mECG and fECG originate from the maternal heart and foetal heart respectively. Their waveforms and beat rhythm is considered independent. Signals measured through multi-lead on the maternal body surface are the mixtures of several sources of signals, including mECG, fECG and random noise. Independent component analysis (ICA) method, also known as blind source separation [6] is currently used in removing random noise and extracting interested signals [2][7] where the mixed multiple signals are statistically independent.

A. ICA Principle

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. 1.

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

$$\boldsymbol{x}(t) = \boldsymbol{A}\boldsymbol{s}(t) \qquad (1)$$

where, $\boldsymbol{s}(t) = [s_1(t) \quad s_2(t) \quad s_3(t)]^T$ $\boldsymbol{x}(t) = [x_1(t) \quad x_2(t) \quad x_3(t)]^T$, $\boldsymbol{A} = ([a_{11} \quad a_{12} \quad a_{13}] \quad [a_{21} \quad a_{22} \quad a_{23}] \quad [a_{31} \quad a_{32} \quad a_{33}])^T$. $\boldsymbol{A}$ is called a "mixing matrix". Superscript T denotes vector or matrix transposition.

The goal of ICA is to find a "separating matrix" $\boldsymbol{W}$, which is as close to $\boldsymbol{A}^{-1}$ as possible, based upon a proper statistical criteria, in order to optimally recover the original source signals as

$$\boldsymbol{y}(t) = \boldsymbol{W}\boldsymbol{x}(t) = \boldsymbol{W}\boldsymbol{A}\boldsymbol{s}(t) \cong \boldsymbol{s}(t) \qquad (2)$$

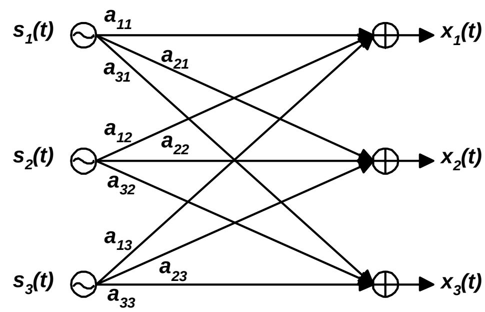

Fig. 1. A simplified ICA model describing the mixture of maternal electrocardiogram (mECG=$s_1(t)$), foetal electrocardiogram (fECG= $s_2(t)$) and random noise (=$s_3(t)$).

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In a simplified ICA model, we suppose that matrix $\boldsymbol{A}$ 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, i.e.

$$p_s(\boldsymbol{u}) = \prod_{i=1}^{3} p_{s_i}(u_i) \tag{3}$$

The mutual information $I(p_y)$ is defined as the Kullback-Leibler divergence between the joint density of all signals and the product of their marginal densities as

$$I(p_y) = \int p_y(\boldsymbol{u}) \left[\log p_y(\boldsymbol{u}) - \log \prod_{i=1}^{3} p_{y_i}(u_i) \right] d\boldsymbol{u} \tag{4}$$

It is clear that $I(p_y)$ 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 $\boldsymbol{y}=g(\boldsymbol{v})=g(\boldsymbol{Wx})$, we have [6]

$$p_y(\boldsymbol{u}) = \frac{p_x(\boldsymbol{u})}{\left|(g')^3 \det(\boldsymbol{W})\right|} \tag{5}$$

Therefore, using observed signals $\boldsymbol{x}$ and selecting a proper contrast function g, $\boldsymbol{y}$ can be optimally separated by minimizing $I(p_y)$ with respect to $\boldsymbol{W}$.

If the joint probability density function of $p_x(\boldsymbol{u})$ and marginal density functions $p_{xi}(u_i)$ 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 $\boldsymbol{W}$ was developed by [1]. Its iterative steps are recapitulated below.

1. Choose an arbitrary (random) matrix as an initial $\boldsymbol{W}$.
2. Let $\boldsymbol{W}^+ = E\{\boldsymbol{x}g(\boldsymbol{Wx})\} - E\{g'(\boldsymbol{Wx})\}\boldsymbol{W}$
3. Let $\boldsymbol{W} = \boldsymbol{W}^+ / \left\|\boldsymbol{W}^+\right\|$
4. If not converged, repeat iteration from step 2.

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

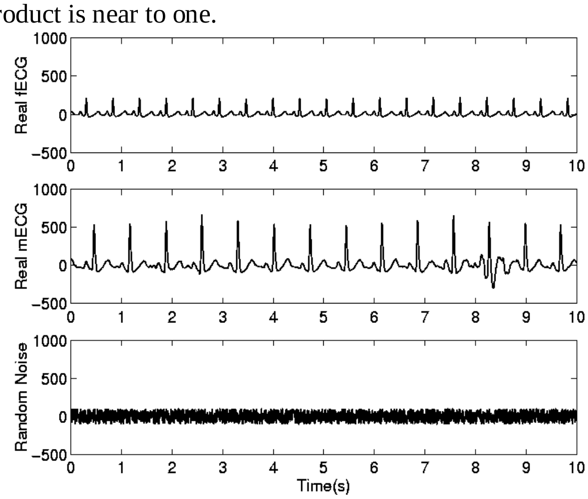

Fig. 2. Original signals for simulation purpose. The first row has a higher heart rate, denotes the fECG. The second row has a longer R-R interval, denotes the mECG. The third row denotes random noise.

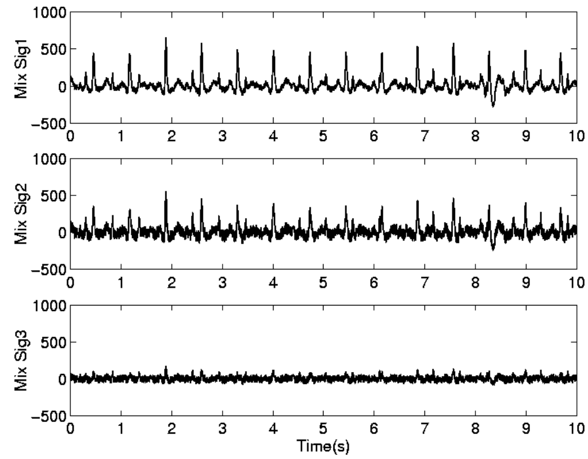

Fig. 3. Mixture of simulation signals using a randomly generated 3×3 mixing matrix. These signals simulate the mixed signals measured by multiple sensors from different leads.

B. Simulation

To verify the fixed-point ICA algorithm and its MATLAB implementation, a set of simulation signals is generated. The original signals are showed in Fig. 2. Signal vector $\boldsymbol{s}(t)$, from top to bottom in Fig. 2, denote the fECG, mECG and random noise, respectively. A 3×3 mixing matrix $\boldsymbol{A}$ is generated randomly and given as below:

$$\boldsymbol{A} = \begin{pmatrix} 0.835 & 0.778 & 0.379 \\ 0.596 & 0.877 & 0.795 \\ 0.129 & 0.334 & 0.526 \end{pmatrix} \tag{6}$$

The mixture signal vector $\boldsymbol{x}(t)$ is created by (1) and the results are showed in Fig. 3.

C. Signal Collection

A pregnant Holstein cow, having gestation period of 177 days, was studied. Two channels of signal were from two abdominal leads. The third signal was from a chest lead. A multi-channel polygraph (NEC Medical System, Model 365) and a digital tape recorder (SONY, PC204A) were used to collect signals. Experimental schema is depicted in Fig. 4. Signals were digitised into a personal computer using a 12-bit A/D converter at 250 Hz sampling rate.

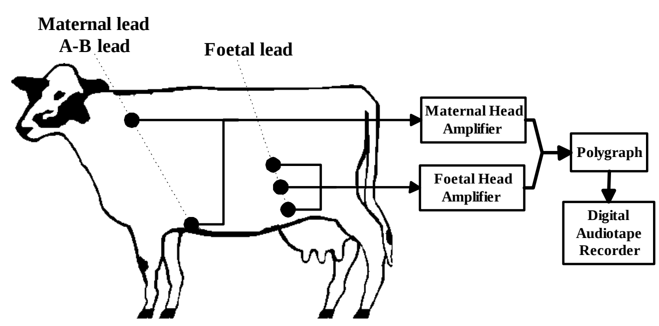

Fig. 4. The experimental scheme and electrodes placement for signal collection. Three channels of signal are collected by three different leads. A chest lead picks up the maternal signal; two abdominal leads collect mainly the foetal signal.

III. RESULTS

The fixed-point ICA algorithm was implemented using MATLAB script. Its performance was examined by both simulation data and measured signals.

A. Simulation Data

Simulation signals showing in Fig. 3 were used as input to the ICA program. Its separation result is showed in Fig. 5. Apparently, the performance of separation is stunning. Nevertheless, The amplitudes of separated signals are completely rescaled. This is because any scalar multiplier in any one of the sources does not affect its statistical independency. As signals are considered as random variables, for simplifying the ICA algorithm and acquiring better convergence condition, input signals are pre-processed, including “centering” and “whitening”, before separation algorithm is applied. Such operations leave the ambiguity in recovered signal’s amplitude and sign. Fortunately, this fault is not always noticeable if only the heart rate is required in this case.

B. *Measured Signals*

Original measured signals from a pregnant Holstein cow is showed in Fig. 6. Top two signals (Ch1 and Ch2) are collected using two abdominal leads. Random noise and maternal component are seen clearly in Ch1 and Ch2. The third channel (Ch3) signal is collected from a chest lead. Its signal quality is somewhat better than that of the foetal signal.

Separation result is showed in Fig. 7. Signals are distinguished into three independent components. Random noise, the foetal ECG and the maternal ECG are showed from top to bottom rows, respectively. The amplitude of any one signal is completely rescaled. Random noise is recognized as one independent component. Random noise in foetal ECG is attenuated and maternal component in it is almost removed as compared to Ch2 in Fig. 6. Thus, there will be no difficulty in using enhanced foetal ECG to detect foetal heart rate.

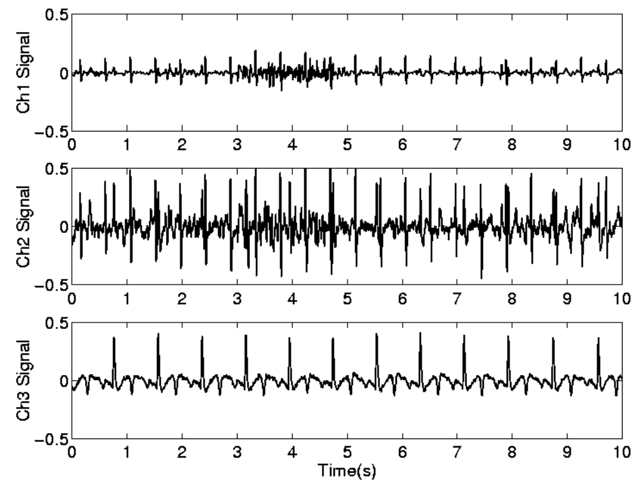

Fig. 6. Measured three channels of signal. Top two signals are from two abdominal leads respectively. The third channel is from a chest lead.

IV. DISCUSSION

Several methods had been proposed to monitor the health status of foetal cattle. Ultrasonic Doppler sensor was inserted into the interior of the rectum to monitor arterial blood flow inside the placenta [5]. Ultrasound echo imaging was also used to detect foetal heart sound [4]. It requires keeping an ultrasonic sensor fixed on the abdominal surface and direct the ultrasonic beam toward the foetal heart. These methods are not suitable for long-term monitoring. We had showed that an adaptive filtering method was effective in enhancing the foetal ECG for foetal heart rate detection [8]. This paper tried an alternative approach to extract the foetal ECG from original noisy measurements. Choosing a proper contrast function is important in separating the target foetal signal. Comparing several contrast functions, we found that a hyperbolic tangent function seems to give the most satisfactory results. This property remains to be studied further.

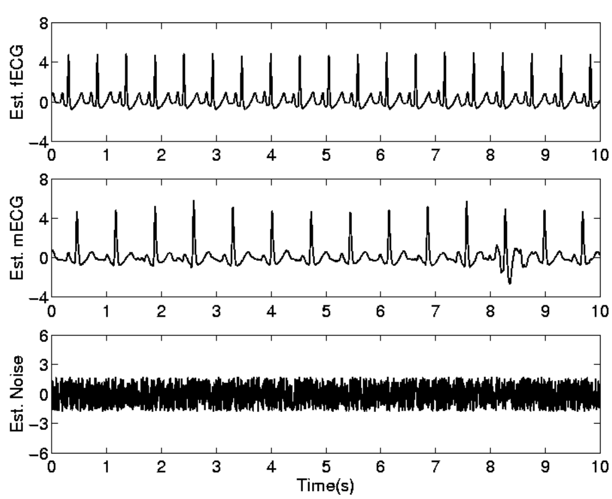

Fig. 5. Separation of simulation signals. Simulated maternal ECG, foetal ECG and random noise are recovered well except for their signal amplitudes are rescaled.

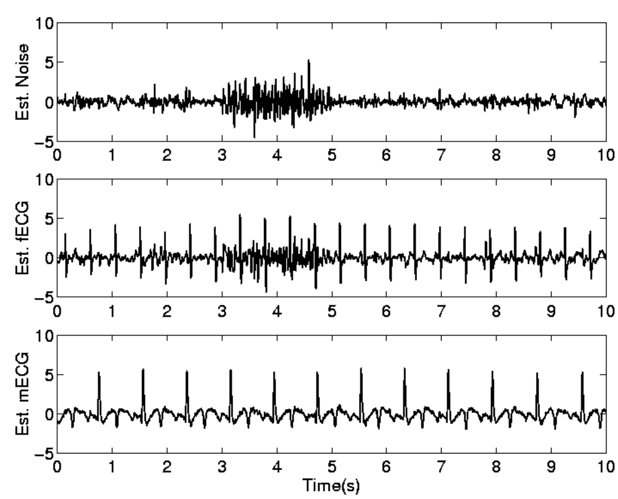

Fig. 7. Separation of maternal and foetal ECG as well as random noise using three-channel measured signals. From the top to the bottom rows, estimated random noise, foetal ECG and maternal ECG are showed respectively.

V. Conclusion

This paper applied the ICA method to detect the foetal ECG, and confirmed its effectiveness by using simulation data and measured signals. The results showed that the ICA is applicable to be utilized in separating foetal ECG from maternal ECG and random noise, because both maternal ECG and random noise are generated from different sources with foetal ECG, these sources can be considered independent stochastically. The ICA method will provide a perspective means for a long-term monitoring of foetal cattle's health status in order to prevent abortion and premature birth, as well as a clue to the prenatal diagnosis.

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