The Fetal Electrocardiogram by Independent Component Analysis and Wavelets

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Abstract: Once the fetal electrocardiogram (FECG) waveforms from ECG on the maternal abdomen are detected, the fetal P wave and T wave cannot always be identified by using continuous wavelet transform (CWT). We took non-invasive FECG from the maternal abdomen, extracted it from the maternal electrocardiogram waveforms after an Independent Component Analysis (ICA), and identified the features of those waveforms by using CWT. We also simultaneously analyzed the observed signals by Primary Component Analysis (PCA). FECG has been extracted by ICA from 25 of 30 pregnant women. The fetal P wave and T wave could be identified in 21 of the 25 cases. FECG was extracted by PCA in only one case. ICA is superior to PCA, whose separation quality highly depends on the careful positioning of the electrodes. We believe that after ICA, FECG obtained by the wavelet theory based method will become a powerful tool for the differential diagnosis of fetal arrhythmias. [The Japanese Journal of Physiology 54: 457–463, 2004]

Key words: fetal ECG (FECG), independent component analysis (ICA), wavelet transforms.

As with adults, the analysis of a fetal electrocardiogram (FECG) would be a reliable method for diagnosing cardiac diseases, especially fetal arrhythmias. During delivery, accurate recordings can be made by placing an electrode on the fetal scalp. However, other methods should be used during pregnancy because of the inaccessibility of the fetus. Ideally, recording FECG from the maternal abdomen is a highly desirable method.

In our earlier report [1, 2], we detected FECG waveforms from ECG on the maternal abdomen by wavelet theory based methods. However, special situations frequently occur not only for the fetal QRS complex superimposed by the maternal QRS complex, but also for the fetal P wave and T wave in close vicinity to the maternal QRS complex. When superimposed by the maternal QRS complex, the fetal QRS cannot be visualized, and also when in close vicinity to the maternal QRS complex, the fetal P wave and T wave cannot be identified by the use of continuous wavelet transform (CWT). To resolve these problems, we resorted to Independent Component Analysis (ICA) to separate FECG from maternal ECG recordings measured on the maternal abdomen. And we also compared the results of ICA with the results of Principal Component Analysis (PCA) [3]. The aim of this article is to show the FECG after ICA and to identify the P wave, QRS complex, and T wave by using CWT. With large fluctuations, we used wavelet-based multiresolution analysis (MRA) to exclude those trends. We also used wavelet thresholding to remove noise.

PATIENTS AND METHODS

Maternal and fetal ECG. It is almost impossible for the naked eye to recognize the admixture of the fetal ECG waveform in standard ECG leads from that of a pregnant woman. The signals were recorded from 8 skin electrodes with the wrist leads placed over the maternal abdomen on both sides of the uterine fundus, the left leg lead placed just above the pubic bone, and the remaining 4 leads placed orthogonally around the maternal abdomen. The ECG data are
obtained as time series data with a BA1008 ECG amplifier (TEAC, Japan). These data are digitized with an EC-2360 A/D converter (Elmec, Japan), acquired by the use of a notebook personal computer and saved as a data file. The sampling frequencies were 2,048 Hz or 5 kHz. After informed consents were obtained, the FECG recordings were performed on 30 women during the 20th week of pregnancy or later.

**Independent component analysis (ICA).** ICA is a new method of multivariate analysis. In the ICA model, the observed data are assumed to be a linear (or nonlinear) mixture of non-Gaussian and mutually independent unknown components (sources). The ICA looks for these sources according to both statistically independent and non-Gaussian characteristics. The observed data matrix \( X \) is considered to be a linear combination of non-Gaussian (independent) source components, i.e., \( X = SA \) where columns of \( S \) (estimated source matrix) contain the independent components and \( A \) is a linear mixing matrix. In short, ICA attempts to ‘unmix’ the data by estimating an unmixing matrix \( W \) where \( XW = S \). The measured signals (\( X \)) will tend to be more Gaussian than the source components (\( S \)) because of the Central Limit Theorem. To extract the independent components, we search for an unmixing matrix \( W \) that maximizes the non-Gaussianity of the sources. In Fast ICA [4, 5], non-Gaussianity is measured by the use of approximations to negentropy \((J)\).

\[
J(y) = \left[ E \{ G(y) \} - E \{ (v) \} \right]^2
\]

where \( v \) is a Gaussian variable of zero mean and unit variance. For the approximations of negentropy, the following choices of contraction function \( G \) have proved useful:

\[
G(u) = 1/\alpha \log \cosh(\alpha u)
\]

where \( 1 \leq \alpha \leq 2 \) is some constant, \( G(u) = -\exp(-u^2/2) \).

The method of Fast ICA by Hyvärinen was used for ICA. The Fast ICA and PCA were performed with the software R, which is a freely available language and environment for statistical computing and graphics. R can be obtained at ‘http://www.r-project.org/’.

**Wavelet transformation.** The wavelet theory is designed to give good time and poor frequency resolutions at high frequencies and good frequency and poor time resolutions at low frequencies. From a one-dimensional input signal \( f(t) \), in this instance the ECG signal, the continuous wavelet transformation is a two-dimensional function of a scale parameter \((a \sim 1/\text{frequency} > 0)\) and a translation parameter \((b = \text{time localization at which the signal is analyzed})\).

\[
CWT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \Psi^*(\frac{t - b}{a}) dt
\]

There are several wavelet functions (mother wavelets \( \Psi(t) \) with \( \Psi^*(t) \) conjugate complex) available with different properties. We analyzed the morphological characteristics of ECG waveforms in the Gabor-8-Power continuous wavelet transform (CWT) [6, 7]. The method of Daubechies [8] was used for discrete wavelet transforms. All analyses were performed with MEM software (Wavelet Analysis and Spectrum Analysis Software [7]).

**Wavelet transform based noise removal.** There is no universal method to reduce noise. Because patterns of noise distribution (the probability distribution function of noise) are different, i.e., Gaussian distribution white noise and uniform distribution white noise, denoising is always a trade-off [9]. Our ECG data with multiresolution analysis (MRA) show that there were several types of noise. To remove these noises, we applied wavelet transform based denoising of the detrended data by MRA up to the 12th level by using Coiflet24 wavelets.

Denoising was performed according to different criteria. Weighted standard deviations of the wavelet coefficients at each resolution level in MRA were used as the thresholds at each resolution level [7]. For example, if the standard deviation of the wavelet coefficient of level 7 is \( \sigma^7 \) and the weighting factor is \( s^7 \), the threshold is given as \( \lambda^7 = \sigma^7 \times s^7 \). We selected weighting factors that made the cost of the information-cost-function (e.g., information entropy, Gauss-Markov entropy, theoretical dimension [7, 10]) as small as possible, and we also selected weighing factors that made the coefficient of determination (square of the correlation coefficient) as large as possible.

**RESULTS**

FE CG has been extracted by ICA from 25 of 30 participants. The fetal P wave and T wave could be identified in 21 of the 25. The FECG has been extracted by PCA in only one case. ICA is superior to PCA, whose separation quality highly depends on the careful positioning of the electrodes. Figure 1 shows the 3.2768 s of a set of potential signals measured in an 8-channel recording. This FECG recording was performed on a 25-year-old woman during her 21st week of pregnancy. The horizontal axis displays the time in seconds; with respect to the vertical axes, only the relative values are important. It means that we can-
not determine the variances (power) of the independent components in ICA. The sampling frequency was 5 kHz. The first column displays the raw data (observed signals are dark gray). The estimated ICA source signals (black) and the PCA source signals (light gray) are shown in the second and last columns. The FECG appears in the ICA 2 (channel 2) and also in the PCA 3. With the exception of this case, FECG and maternal ECG could not be separated by PCA. The maternal ECG is recognized in ICA1 and 3. The interesting components are drawn and magnified from the signals in the raw data (Fig. 2). Row 1 (dark gray) of each column on the figure corresponds with os 2 (raw data in Fig. 1), which includes the signals coming from both the maternal and the fetal heart. The estimated source signals after ICA are shown in rows 2, 3, and 4 (black) of the left column where FECG appears in row 3. The results after PCA (up to the 3rd primary component) are displayed in rows 2, 3, and 4 (light gray) of the right column. FECG is also recognized in row 4. The FECG waveform (ICA2 in Fig. 2) is shown in Fig. 3 before and after denoising by wavelet. The gray line is the signal before denoising, and the black line is the signal after wavelet transformation based denoising. In CWT (Figs. 4 and 5), the fetal QRS complex has narrow, elongated gourd-shaped features and knots corresponding with the P wave and the T wave that can be seen in the CWT of typical ECGs, as described previously [1, 2]. The case we have reported in this article is exceptionally valuable because the FECG has been extracted separately either after ICA or after PCA. This opportunity can be used to estimate how the important component (PCA3 in Fig. 2, corresponding to the FECG signals) occupies an important position in the PCA. The proportion of variance of PCA3 (the 3rd principal component, FECG) in the PCA is estimated to be about 10.9%, and the 1st and 2nd principal components are 44.9% and 20.7%, respectively. PCA is possible under the implicit concept that variance (power) is information. This result does mean that the power of the signals in the PCA does not necessarily cor-
DISCUSSION

Just as an ECG is useful in diagnosing cardiac diseases in adults, the analysis of FECG could be a reliable method for diagnosing cardiac diseases, especially fetal arrhythmias. Potential recordings taken on the maternal abdomen are affected not only by large baseline fluctuations (caused by several bio-electric phenomena), but also by various types of noises (such as intrinsic noise from a recorder and noise from electrode-skin contact). This makes it difficult to discriminate between FECG waveforms and extraneous noise. The FECG and maternal ECG waveforms in cutaneous potential recordings are overlapping in time and frequency. This is why a separation of these signals cannot be realized by simple windowing or linear filtering. And the parametric formulation of the quasi-periodicity of a regular heart rate pattern would hamper the detection of arrhythmias. In this instance,
A good separation of FECG was demonstrated after PCA. To enable a good separation, however, it seems crucial to choose the electrode positions in a way that virtually corresponds to an orthogonal transfer, that is, when the mixing matrix has mutually orthogonal columns, or to realize a situation where the source variances are very different. In these exceptional situations, the result after PCA has been mathematically proved to be equal to that after ICA [11]. Therefore ICA is much more superior to PCA in practical usage. ICA can achieve the direct reconstruction of the different statistically independent source signals and also characterize their propagation to the electrodes, which should bring us more important medical information than ever. In these respects, ICA is a very promising technique, but its clinical applications are still in the early stages. In clinical practice, the FECG can become a decision support tool combined with electronic fetal heart rate (FHR) monitoring [12, 13, 14]. FHR monitoring, introduced in the 1960s, made clinicians anticipate that this technique would prevent suffering from asphyxia-induced brain damage or death in the newborn. However, we now realize that FHR monitoring does not provide improvement.

Fig. 4. Continuous wavelet transformation (CWT) of signals in ICA2 after denoising. The positions of the P wave and T wave can be inferred from the feature of CWT. If a vertical line is drawn up from the position of the P wave and T wave of the image, the intersection point with the original FECG waveform is the position of the P wave and T wave.
in the outcome of a newborn, but it does cause an increase in cesarean deliveries [15]. The poor specificity of FHR pattern interpretation has resulted in a search for the new method. Among the various approaches, FECG after ICA is the most attractive method. However, the initial works [11, 16, 17] carried out by using ICA has until now depicted only the fetal QRS complex; it could depict neither the fetal P wave nor the T wave visually. In contrast to these works, we can extract the fetal QRS complex, P wave and T wave by the wavelet theory based method after ICA. Therefore our method could play an important role in evaluating the well-being of the fetus and in diagnosing fetal cardiac diseases.

We believe that FECG by wavelet theory based methods after ICA will become a powerful tool for the differential diagnosis of fetal arrhythmias.

REFERENCES