# Using Wavelet Transformation in Blind Sources Separation of the Fetal Electrocardiogram

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**ABSTRACT**:
One of the most important problems in heart signal processing is the extraction of the fetal electrocardiogram (FECG). One of the reasons that we are interested in FECG extraction is that this signal consists of important characteristics about healthy conditions of the fetus. Based on available conditions, Blind Source Separation is a suitable method for this problem. Existence of noise in observed signals from electrodes on the mother's body, can affect the separation performance. Therefore, signal de-noising is an important stage in this problem. In this study, using wavelet transform and optimum selection of its parameters in FECG extraction has been investigated. The first reason for using wavelet transform is to remove noise from the observed signals and the second reason is to apply it into BBS algorithms. Depending to the noise level in signals, wavelet transform can be used before or after signal separation, also it can be used both before and after signal separation. Simulation results show the performance of each method in different conditions for obtaining the desired signal at the presence of noise.

**KEYWORDS:** Wavelet Transformation, Blind Sources Separation, Heart Signal, Thresholding.

## 1. INTRODUCTION

The problem of processing heart signal has been studied since 1950s. The first studies concerned this problem had been performed by Marvell [1]. Using averaging out methods, he performed the processing heart signal by utilizing Cross Correlation Function, and Fast Fourier Transform.

Separation of the fetus-electrocardiogram (FECG) from the electrocardiogram (ECG) obtained from mother's heart is among the most applicable issue regarding ECG signal processing. Among reasons, we opt to separate FECG from the resultant composition is that FECG signal contains important indexes about fetus health conditions. The two important indexes gained from ECG are composition of FECG and MECG and noise at one hand and fetus heart rate variation (FHRV) at the other hand [2].

ECG signal is composed of a synthesis called PQRST produced through heart's muscle contraction and contains three following sections.

1. P waveform that is the result of heart's muscle contraction.
2. QRS compound achieved from ventricular contraction and is recognizable regarding R magnitude.
3. T waveform resulted from phase change in every hearth contraction.

Although PQRST signal is accessible, physicians opt to get it before surgery. One way to achieve FECG is getting it through fetus skull. In spite of being exact, this method needs accessing to fetus skull. Another method is to gain it through mother's abdominal parts. This method does not need direct accessing to fetus skull; however, considering some signals existence like mother heart signal (MECG), mother's breath, heat noise generated by receivers, and so on it is no precise and needs some techniques to achieve net FECG from it.

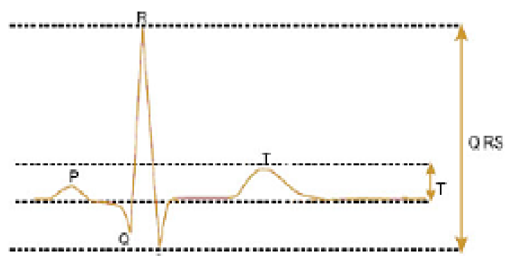


**Fig. 1.** PQRST waveform

Fetus heart beating frequency is nearly 1 to two times greater than mother's heart beating frequency. Hence, the first assumption is conducting an analysis of their frequency domain and using an optimum filter for separation; however, respecting overlapping, MECG and FECG signals do not show necessary effectiveness. (The main fetus heart beating frequency is almost 2Hz and overlapped with MECG first harmony). Moreover, because of different factors, heart beating period may experience some variations too and as a result using a filter is not logical for this case.

Abboud showed that the averaging out method to process of fetus heart signal is not a proper method, because the fetus heart signal obtained from the averaging method doesn't define the real time duration of waves shape in signal [3].

With respect to the mentioned cases and this fact that the quality of these signals compositions varied regarding different body conditions (channel undefined); we may therefore define the blind sources separation algorithm as a proper method here [4].

Blind source separation is the separation of signals from several sources, which had been received after crossing an uncertain channel.

Using wavelet transformation today is also one of the important discussions in signal processing. Specific capabilities of this transformation had changed it to one of the most applicable transformations in the time-frequency domain. Omission of the noise from the signal is one way to make use of wavelet transformation. Omitting the noise from the signal by transforming wavelet comes from the idea that wavelet coefficients associated with noise signal would have small quantity compared to wavelet coefficients associated with original signal by exerting wavelet transformation on some noisy signal, thus the noise would be omitted and original signal renovated by causing small coefficient, obtained from wavelet transformation and restoration the reverse wavelet transformation from the coefficient produced, becoming zero.

To improve the performance, therefore the combination of wavelet transformation and blind source separation in fetus heart signal processing can be used.

## 2. Blind Sources Separation

Transmission from an electrical source to an electrode in body surface may be considered as a linear approach. Therefore, if X is an observation's vector by electrodes and S is sources signals vector and A is also considered as transmit matrix. The the following relation is achieved: X=AS

About transmit matrix (A), in case of ECG, it is notable that matrix will experience some changes regarding fetus growth, its movement, and change in the environment features and therefore, in respect to body structure, position of sources and electrodes and also electrical conductivity of body's different strings may be defined. Various algorithms in the field of BSS are now used to separate ECG signals. ICA algorithm is a proper one for this case. We may refer to another suggested algorithms like INFOMAX, JADE, and MERMAID [5]. We deploy the idea of using wavelet transformation in blind Sources separation. Appropriate signals are fetus heart signal and mother heart signal that after passing a channel (linear) and combining with a current noise get access to electrodes positioned over mother's body surface.

Operations regarding wavelet transformation may be done before or after the separation. Even it may be used before or after the separation process. FastICA algorithm is also used for this separation too [6], [7].

In case of no noise, separation of the above-mentioned signals may result in fig 2.

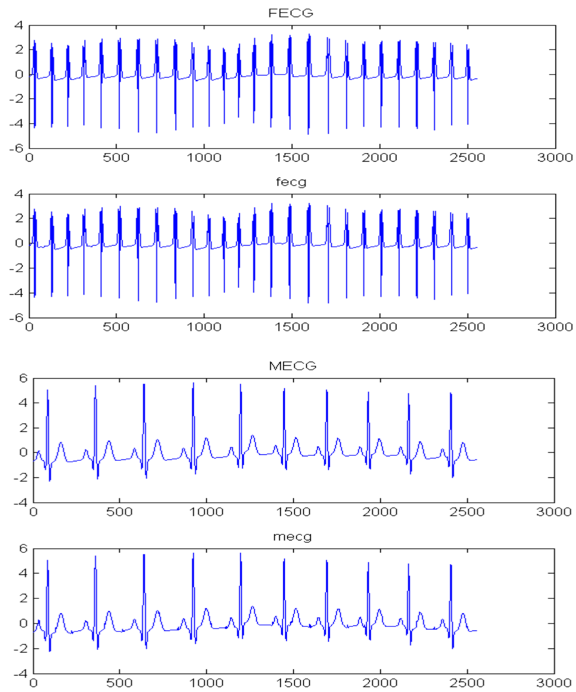


**Fig. 2.** Separated signals in no-noise existence case

Fecg (fetal electrocardiogram), mecg (maternal electrocardiogram) are reconstructed waves figure, and FECG and MECG are the main wave figure.

It is shown that using BSS algorithms for separation will achieve good results in case of no-noise existence.

## 3. Using Wavelet Transformation in Blind Sources Separation

Existence of noise in the observed signal may extremely affect separation function. Therefore, noise removal from the signal is one of the main issues in discussion of the blind Sources separation algorithm[8]. Through wavelet transformation, signal data are gathered in wavelet's great coefficients. Therefore, using a threshold limit and filtering of existed coefficients and then signal reconstruction through reverse wavelet transformation, the main part of existed noise alongside those signal's parts experience quiet changes are removed from the signal [9]. The important point here is the proper choice of wavelet function, coefficients thresholding function and finally the most important one that is the threshold limit. In addition to noise removal, wavelet transformation may be used for transformation of a vector to 3D orthogonal-based vectors resulted in optimization of separation algorithms. Hence, we may take advantages of both through combining wavelet transformation with BSS algorithms [10], [11].

## 4. SIMULATION RESULTS

Figure 3 shows blind Sources separation results where noise is existed.

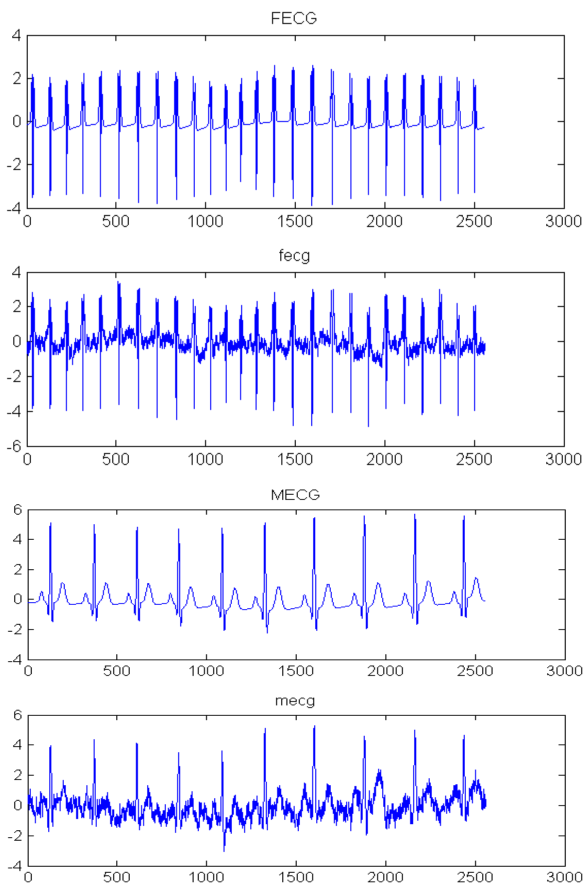


**Fig. 3.** Separated signals in noise existence case

fecg, mecg are reconstructed waves figure, and FECG and MECG are the main wave figure.

In this case, it is shown that BSS algorithms are not able to separate signals optimally, and hence we have to use some forms of transformations in order to remove noise. Figure 4 shows results achieved from separation due to conducting wavelet transformation before the separation. As it is shown, by using this technique, noticeable improvement is achieved in separation procedure.

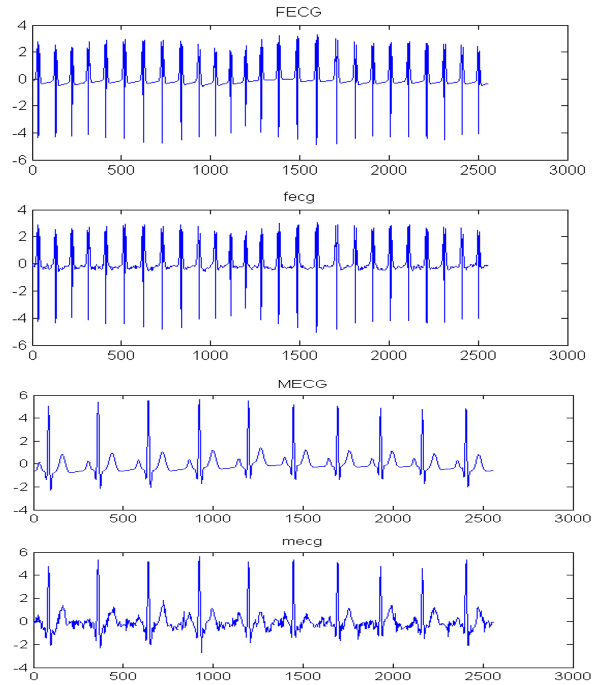


**Fig. 4.** Separated signals after conducting wavelet transformation before separation

Figure 5 shows results got from wavelet transformation procedure after separation. As it is shown, using this technique, separated signals are also very close to the actual form.

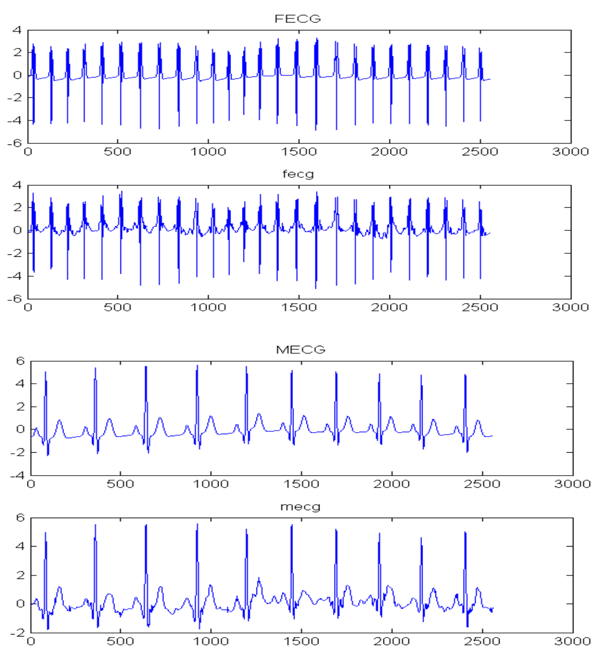


**Fig. 5.** Separated signals after conducting wavelet transformation after separation

fecg, mecg are reconstructed waves form, and FECG and MECG are actual waves form.

Finally, at the last stage, we conduct wavelet transformation before and then again, after separation over the signals (figure 6).

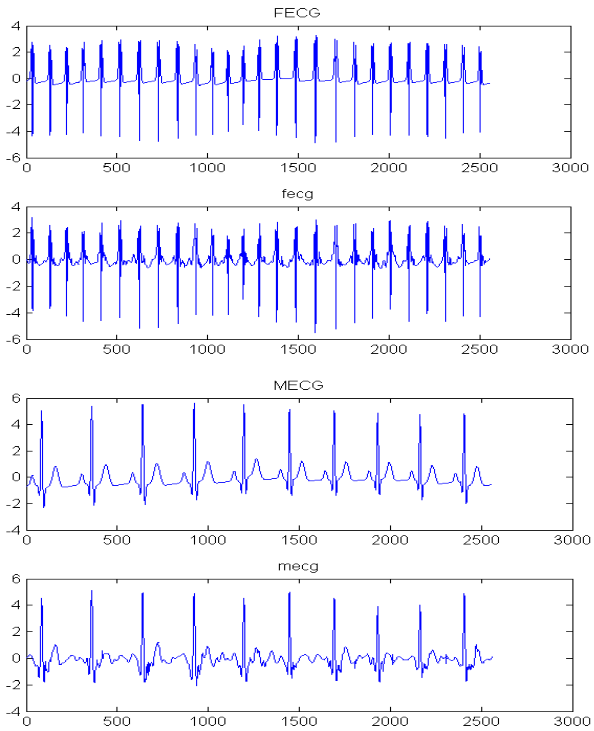


**Fig. 6.** Utilizing wavelet transformation before and then after the separation

Fecg and Mecg are reconstructed waves form, and FECG and MECG are actual waves form.

Using this method, we may remove residual noise from separated signals.

In this study, we investigate the wavelet transformation role in blind separation of sources. There are two important points here. One deals with the choice of wavelet transformation parameters for its optimum functionality and the other is the quality of using wavelet transformation in blind sources separation of ECG signals. Through wavelet transformation and taking advantages of different parameters, we may finally assert that by using (dbN) functions for N=3,…,6 and biorthogonal functions as the wavelet function and hard thresholding and choosing threshold limit through Rigrsure method, for separation of ECG signals, the expectation for getting the best results is within reach.

In the model: X(t)=AS(t)+N(t) and through definition of PRD as follows:

$$PRD = \sqrt{\frac{\sum_{i=1}^{N}[N(i)]^2}{\sum_{i=1}^{N}[x(i)]^2}} \times 100\%$$

That is somehow an index of noise quantity.

**Table 1.** PRD values (percent) for wavelets and various threshold selection functions.

| mother wavelet | Threshold limit selection function | | | |
|---|---|---|---|---|
| | Rigrsure | Sqtwolog | Minimaxi | Heursure |
| Db6 | 66.2 | 93.5 | 69.86 | 73.54 |
| Db3 | 66.9 | 91.03 | 69.25 | 76.98 |
| Haar | 70.24 | 97.33 | 72.79 | 82.98 |
| Coif5 | 67.2 | 90.8 | 68.85 | 72.42 |
| Sym4 | 66.67 | 87.88 | 68.37 | 73.43 |
| Bior1.1 | 69.1 | 98.3 | 70.37 | 87.3 |

PRD primary value: 78.82%

**Table 2.** PRD values (percent) for various thresholding functions. (wavelet: db6, threshold limit selection function: Rigrsure)

| Thresholding function | PRD primary and secondary values | | | |
|---|---|---|---|---|
| | 55.15 | 40.53 | 26 | 18.8 |
| Hard | 44.3 | 33.8 | 25.2 | 17.5 |
| Soft | 50.8 | 36.3 | 27 | 19 |
| Garrote | 45.75 | 34.7 | 25.7 | 20.6 |

**Table 3.** PRD values (percent) for wavelets and various threshold selection functions

| mother wavelet | PRD based on threshold limit selection function | | | |
|---|---|---|---|---|
| | Rigrsure | Sqtwolog | Minimaxi | Heursure |
| Db6 | 36.2 | 51.1 | 39.57 | 40.81 |
| Db3 | 36.4 | 49.4 | 38.45 | 43.6 |
| Haar | 37.45 | 52.2 | 38.32 | 46.11 |
| Coif5 | 36.42 | 51.12 | 37.84 | 51.12 |
| Sym4 | 36.13 | 48.23 | 37.53 | 48.23 |
| Bior1.1 | 36.15 | 51.3 | 38.43 | 47.38 |

PRD primary value: 41.27%

**Table 4.** PRD values (percent) for different advancing levels of wavelet transformation (wavelet: db6, threshold limit selection function: Rigrsure, hard thresholding function)

| No of stages | PRD primary and secondary values | | | |
|---|---|---|---|---|
| | 55.2 | 40.5 | 26 | 18.8 |
| 5 | 50.6 | 36.4 | 24.3 | 18.2 |
| 6 | 44.3 | 33.8 | 22.1 | 18.2 |
| 7 | 45.51 | 33.6 | 22.2 | 18.7 |
| 8 | 47.7 | 34.9 | 23.2 | 18.3 |
| 9 | 48.9 | 35.7 | 23.3 | 18.9 |

**Table 5.** PRD values (percent) for different wavelet transformation application methods and FastICA algorithm (wavelet: db6, threshold limit selection function: Rigrsure, hard thresholding function)

| | PRD primary and secondary values | | | | | |
|---|---|---|---|---|---|---|
| | 14.2 | 17.3 | 26 | 33 | 40.53 | 55.18 |
| Wavelet transformation before separation algorithm | 11.73 | 14.4 | 23 | 29.5 | 33.8 | 44.3 |
| Wavelet transformation after separation algorithm | 11 | 14.1 | 24.6 | 31.6 | 38.2 | 49.6 |
| Wavelet transformation in pre/post phase of separation algorithm | 11.5 | 14.2 | 22.4 | 28.3 | 28.7 | 37.2 |

**Table 6.** PRD values (percent) for applying various methods of wavelet transformation FastICA algorithm (wavelet: db3, threshold limit selection function: Rigrsure, hard thresholding function)

| | PRD primary and secondary values | | | | | |
|---|---|---|---|---|---|---|
| | 14.2 | 17.3 | 26 | 33 | 40.53 | 55.18 |
| Wavelet transformation before separation algorithm | 11.9 | 15.1 | 24.2 | 30.1 | 36 | 46.2 |
| Wavelet transformation after separation algorithm | 11.5 | 14.7 | 24.8 | 33.8 | 39.7 | 51.6 |
| Wavelet transformation in pre/post phase of separation algorithm | 11.6 | 14.6 | 23.2 | 29 | 32.3 | 41.4 |

## 5. Conclusions

It is shown that for PRD less than 25%, the best results will be gained through using wavelet transformation after accomplishment of the separation process. For PRD of about 40%, using wavelet transformation, before separation, goes along with more optimized results; and finally for PRD more than the above-mentioned percents, it seems that we should use wavelet transformation, both before and after the separation, in order to remove the noise.

In other words, we may express that the existence of heavy noise in the signal, resulted in confronting more difficulties in performing the process. Therefore, in low noise case, we may use the separation algorithm and then perform the wavelet transformation over the resultant signals in order to remove existed noise. For the case, that noise signal is tangible, we should firstly, remove noise from the signal. If there is noticeable noise in the signal, there existed some noise in the resultant signals after accomplishment of the separation process; the phenomenon that makes using wavelet transformation technique for removal of residual noise inevitable.

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