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ROBUST FETAL HEART BEAT DETECTION BY APPLYING STATIONARY WAVELET TRANSFORM

Bogdan HUREZEANU*[1], Dragoş ŢARĂLUNGĂ*[2], Rodica STRUNGARU[3], Ilinca GUSSI[4], Werner WOLF[5], Mihaela UNGUREANU[6]

Fetal electrocardiogram (fECG) analysis, i.e., the analysis of the heart rate (HR) and the fECG morphology, offers clinicians vital information about fetal health condition. The fECG can be acquired non-invasively by applying electrodes on maternal abdomen, but the recorded abdominal signal (ADS) contains not only the signal of interest, fECG, but also some physiological (e.g., maternal electrocardiogram) and non-physiological (e.g., power line interference (PLI)) signals, that prevent the direct fECG analysis. An algorithm is proposed for fetal HR extraction, based on stationary wavelet transform (SWT) and independent component analysis (ICA). It is evaluated on real ADS showing good results even for high noise levels.

Keywords: fetal ECG, SWT, ICA, QRS detection

1. Introduction

Antepartum fetal health is nowadays evaluated with the help of many different parameters, the most used one being still the fetal heart rate (fHR). The antepartum monitoring of the fHR enables clinicians to early diagnose situations when the fetuses are at risk, offering them the chance to act timely. The fHR can be derived directly from the fetal electrocardiogram (fECG) which can be obtain via a noninvasive method by placing electrodes on the maternal abdomen to record the abdominal signals (ADS). Similarly as for the adult electrocardiogram

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* B. Hurezeanu and D. Taralunga equally contributed to the publication and therefore both are considered as first authors

[1] PhD student., Dept.of Applied Electronics, University POLITEHNICA of Bucharest, Romania, e-mail: bogdan.hurezeanu@gmail.com

[2] PhD, Dept.of Applied Electronics, University POLITEHNICA of Bucharest, Romania, e-mail: dragos.taralunga@upd.ro

[3] Prof., Dept.of Applied Electronics, University POLITEHNICA of Bucharest, Romania, e-mail: rodica.strungaru@upb.ro

[4] PhD, Dept.of Obstetrics and Gynecology, University of Medicine and Pharmacy Carol Davila, e-mail: ilinca.gussi@gmail.com

[5] Prof., Institut für Infomationstechnik, Universität der Bundeswehr, Munich, Germany, e-mail: Werner.Wolf@unibw-muenchen.de

[6] Prof., Dept. of Applied Electronics, University POLITEHNICA of Bucharest, Romania,: e-mail: g.mihaela.ungureanu@upb.ro

(ECG), the fECG reflects the fetal heath condition, but it cannot be analyzed directly from the ADS, being corrupted by different types of disturbances: the power line interference (PLI), the baseline wander, the electrical activity of the abdominal muscles (EMG), and the maternal ECG (mECG). Moreover, the fECG is also overlapping with the noise sources also in the frequency domain, thus complex algorithms are necessary for an efficient fECG extraction. The mECG is the strongest disturbing signal, having complex QRS amplitudes up to 20 times that of the fQRS [1].

The fQRS complex is the most prominent component the fECG signal, thus its detection is used for deriving the fHR [2]. Nevertheless, fHR derived from a corrupted fECG can lead to inaccurate diagnostics, thus, a clean fECG is mandatory. The proposed algorithm shows improved results in detecting the fQRS when the ADS are corrupted, using the SWT and ICA. An evaluation on real ADS signals recording is performed, where the influence of SWT is discussed.

2. Methodology

A. Stationary Wavelet Transform

The wavelet transform is an improved method to detect and analyze abrupt changes of the signal. It is a time-frequency decomposition that uses the wavelet function to characterize the signal [3]. By considering

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), \qquad a = 2^k, k \in N, b \in R \tag{1}$$

ψ being the mother wavelet, a- the scaling parameter and b- the shifting parameter, Wavelet transform converts any signal to a representation using wavelets in terms of scale and translation. The output is a description of the signal at different scales. The purpose of the transform is to focus on certain features at specific scales independently.

The wavelet transform is calculated for the time-domain signal at different frequencies and offers a good resolution for high frequency components even for short duration signals and low frequency components for long durations. For a projection of the wavelet basic, the wavelet transform can be defined as

$$T(a,b) = \int x(t)\psi_{a,b}(t)dt \tag{2}$$

The QRS complex (that is part of the ECG) is characterized as a low frequency signal, ranging from about 1 Hz up to 45 Hz [4]. This property can be used when applying the wavelet transform. Choosing the right scale, the noise can be much reduced, enhancing thus the signal of interest. Let us consider that the analyzed signal is $x[n]$, with N samples, where $N = 2^j$, j being an integer. The approximation coefficients, c_i , and the detailed coefficients d_i , are defined for a sequence x using two filter functions, h and g, that correspond to low and high pass filter, respectively. This is can be represented as a binary tree as seen in Fig.1 with nodes representing a sub-space with a different time-frequency localization.

$$c_i[n] = (h * x)[\mathrm{n}] = \sum_k x[k]\,\mathrm{h}[n-k] \tag{3}$$

$$d_i[n] = (g * x)[\mathrm{n}] = \sum_k x[k]\,g[n-k] \tag{4}$$

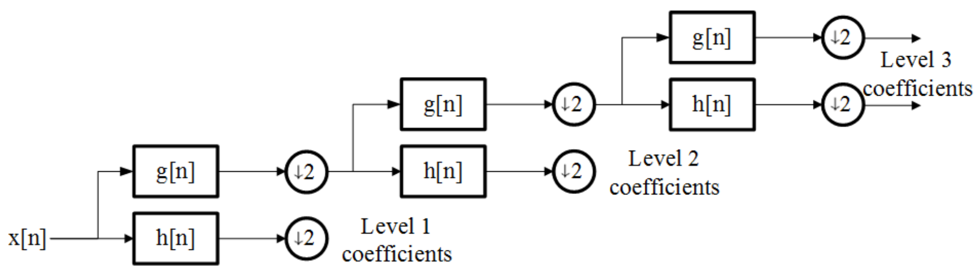

Fig. 1 The tree structure or filter bank of the DWT

The SWT is similar with the Discrete Wavelet Transform (DWT) except that the output signal is not downsampled, i.e. not decimated [5]. By downsampling, the even or the odd samples are selected, affecting the time variance, this being critical in the biosignal processing, especially when analyzing the weak fetal ECG. Thus, the morphology of the output signal is not affected by the SWT unlike by the DWT. The SWT method is recommended when the white noise is present, having better results than DWT or continuous wavelet transform (CWT) [6]. Overall, the main application of the SWT is denoising. When SWT is applied, the two new sequences corresponding to high and low frequencies, have the same length as the original.

The translation invariance is restored with the help of ε-decimated element, which is the choice of odd or even indexed items at step j and labeled by a sequence of 0 and 1. In DWT, the signal is convolved and decimated. Computationally more complex, the SWT represents the shifted DWT coefficients, by modifying the filters at each level. The filters at each level are up-sampled versions of the previous stage.

$$c_{j+1}[n] = (h_{j+1} * c_j)[\mathrm{n}] = \sum_k c_j[k]\mathrm{h}_{j+1}[n-k] \tag{5}$$

$$d_{j+1}[n] = (g_{j+1} * d_j)[\mathrm{n}] = \sum_k d_j[k] g_{j+1}[n-k] \tag{6}$$

C. Independent Component Analysis (ICA)

ICA is a blind source separation technique that enables the decomposition of a mixture of signals into statistical independent components. The use of ICA to obtain the fECG from the ADS signal is explained in [7-9].

An ICA model can be defined as

$$\boldsymbol{x} = \boldsymbol{A}\,\boldsymbol{s} + \boldsymbol{n} \tag{7}$$

where n is the uncorrelated Gaussian noise n~ N(0,diag(∑)), x is the observations vector, s defines the sources and A the mixing matrix. As the ADS represent the mixtures of different sources from the abdomen, the ICA technique is a great tool to obtain the original sources. The most used ICA algorithm is Joint Approximate Diagonalization of Eigen-matrices (JADE), that uses a tensor to diagonalize the observations statistics and to obtain the inverse matrix [10]. The JADE algorithm comprises the following steps:

i. **Initialization**

An initial weighting matrix is constructed from the diagonal matrix of the eigenvalues (V_L) and eigenvectors (V_C) of the covariance matrix $\mathbf{R}_x$=E(X*X^T), where E is the mathematical expectation function and X the vector composed of observed signals.

$$\boldsymbol{W} = \boldsymbol{V_C} \cdot \boldsymbol{V_L}^{(-\frac{1}{2})} \cdot \boldsymbol{V_C}^T \tag{8}$$

ii. **Maximization of the cumulant matrix** Q_x

For the vector X with n components and a n × n matrix M, we define the associated cumulant matrix $Q_x(\boldsymbol{M})$) as the n × n matrix defined

$$Q_X(\boldsymbol{M}) = E\{(\boldsymbol{X}^T\boldsymbol{M}\boldsymbol{X})\boldsymbol{X}\boldsymbol{X}^T\} - \boldsymbol{R}_X tr(\boldsymbol{M}\boldsymbol{R}_X) - \boldsymbol{R}_X\boldsymbol{M}_X - \boldsymbol{R}_X\boldsymbol{M}^T\boldsymbol{R}_X \tag{9}$$

where tr() is the trace of the matrix.

iii. **Optimization of the orthogonal contrast.**

$Q_X(\boldsymbol{M})$ has to be diagonal, and with the help of an orthonormal transform V, the rotation matrix $\boldsymbol{U}$ is identified to achieve

$$\boldsymbol{U} = argmin \sum_i Off(\boldsymbol{V}^T \boldsymbol{Q}_X \boldsymbol{V}^T) \tag{10}$$

iv. **Estimation of the mixing array A**

$\mathbf{A}$ is computed as $\mathbf{A} = \boldsymbol{V}\boldsymbol{W}^{-\mathbf{1}}$ and the sources as $\mathbf{S} = \mathbf{V}^T\boldsymbol{W}\boldsymbol{X}$

In the ADS case, the sources are the fetal and the maternal heart, the uterine muscles, the PLI and the abdominal muscles. The conductive medium is considered homogeneous and all the other remaining signals will be separated as noise by ICA.

D. QRS Detection

The QRS characteristic points (onset, peak and offset) are detected within three scales that are automatically linked to the ECG energy. The fiducial points are set and a segmentation of the original signal can be performed. This procedure is useful also in ECG morphology identification as it offers a reliable method to identify the ECG wave. Noise sources like baseline wander, PLI and muscle activity have similar frequency content as QRS complex.

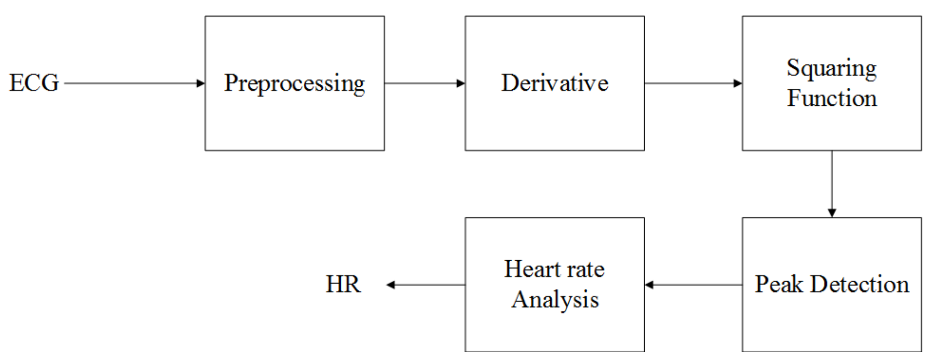

Fig. 2 Pan-Tompkins algorithm block

In order to detect the true QRS peaks and to remove the false negative and false positive, parameters like slope width or amplitude threshold are used. The Pan-Tompkins algorithm was adapted for the fetal QRS detection [11, 12] (Fig.2). Yet this method should be used carefully as the high noise can corrupt these parameters.

Even if the modern bio-amplifiers have a high common mode rejection ratio (CMRR) and high input impedance, the ADS signals are still contaminated by the residual noise signals [13]. For weak signals like ECG, filtering is mostly applied solution, which has an impact on the performance and on the accuracy of the ECG processing algorithms. Analog filters can introduce phase shifts, skewing the signal, whereas the digital methods are more flexible if no absolute realtime processing is required. Researchers have shown that a 40db notch filter with a bandwidth of 4 Hz is altering the QRS complex as well [14]. Not only the fundamental frequency, but also the harmonics can be present within the PLI. A comb filter noise canceller is used to remove the PLI from the ADS and to preserve the fetal information. This approach is not based on an external reference, extracting the PLI components by band-pass filtering.

3. Experimental data

In this study, 12 abdominal electrodes were used, the recordings being performed at "Ioan Cantacuzino Hospital", in Bucharest. An ultrasound investigation was conducted before to localize the fetal position. In order to have a good resolution a sampling rate of 1000 Hz was used. Thoracic mECG signals were also recorded to evaluate the mECG contributions to the ADS. In order to have a successful ICA extraction, the number of observations, or recording channels, must be greater than the number of sources.

The fetal QRS starts at 20 Hz, whereas the mother QRS ranges from 10 Hz up to 40 Hz [1-2]. The fECG overlaps not only the maternal ECG but also other disturbing signals as depicted in Fig.3. Fig. 4 illustrates the algorithm functionality, where the SWT eliminates the frequencies that are interfering with the signal of interest. A preprocessing step is required to improve the SNR, which implies the removal of power-line interference and the artefacts resulting from the recording setup. The mother wavelet was chosen by considering the number of vanishing points and the similarity with the ECG. Experimental tests showed that Daubechies wavelet db8 generates the smallest error, with similar results from db3 and db4 (Fig.6). All these wavelets share asymmetric properties and their efficiency does not depend on the coefficients' values.

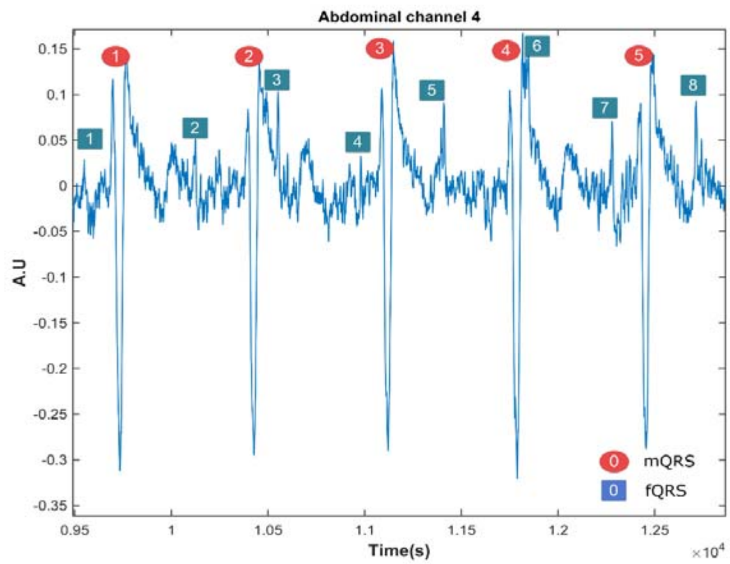

Fig. 3 Abdominal signal channel 4 with manual QRS marking

The time invariance property enabled by SWT/ Inverse SWT (ISWT) is particularly important in statistical signal processing such as detection or parameter estimation of signals with unknown arrival time. The thresholding block is used on wavelet coefficients in order to enhance the estimation of the unknown signal. The SWT compress the signal of interest and spreads the noise.

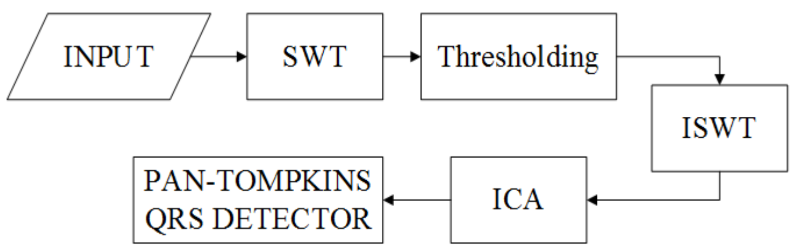

Fig. 4 Block diagram of the algorithmic concept

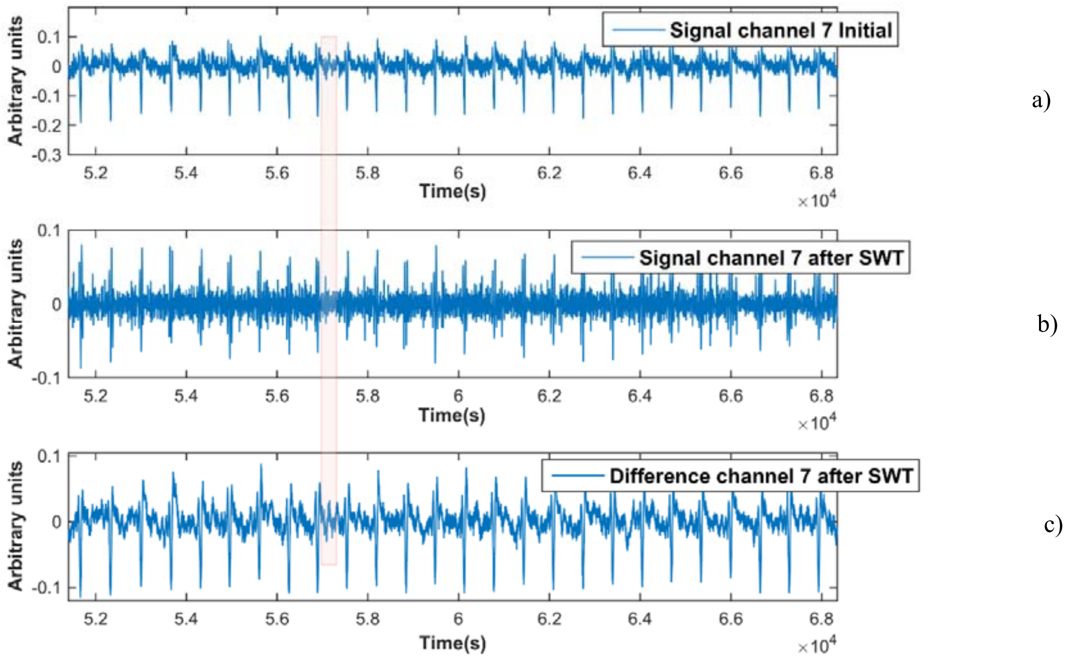

Fig. 5 Components that were not interfering with the fetal QRS were removed. a) presents the preprocessed signal, b) the output of the wavelet transform block for the signal and c) illustrates the difference between the input and output

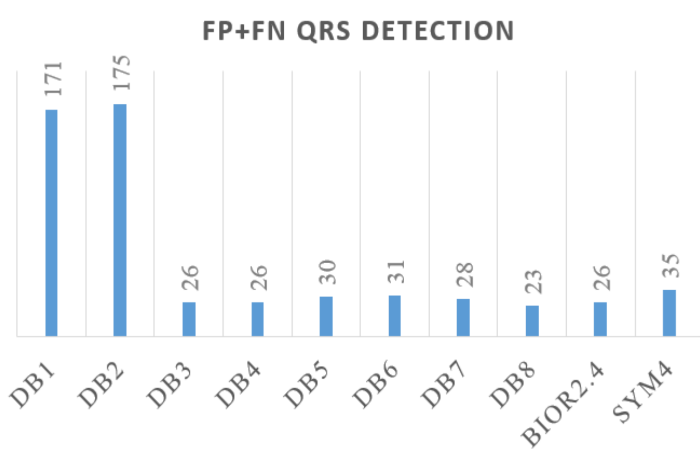

Fig. 6 QRS errors of the algorithm depending on the mother wavelet

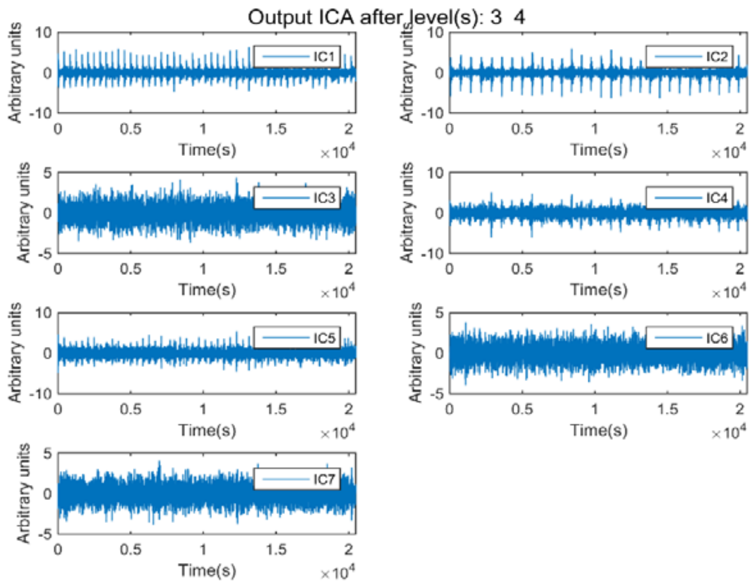

Fig. 7 Independent components obtained from the reconstructed signals after the wavelet transform. Now the energy of the fECG is higher in comparison to the sources. IC1 and IC5 show fetal information, whereas the maternal activity is detected in IC2 and IC4

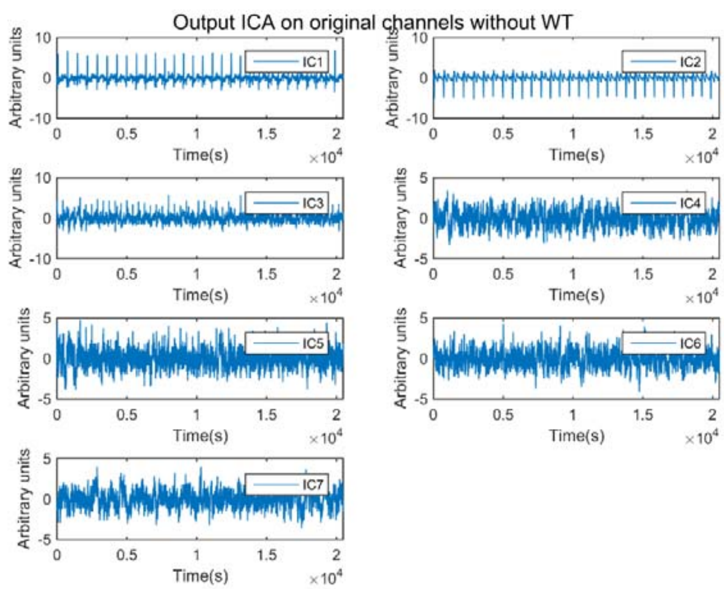

Fig. 8 Independent components without SWT. Only IC3 shows fetal information

Table 1

QRS Complexes detected within a 200 s frame

	FP QRS	FN QRS	ERROR	TOTAL QRS DETECTED	ACCURACY (%)
SWT+ICA	12	3	15	488	96.9
ICA	87	46	133	496	72.2

A comparison between the fHR detected using only ICA and the fHR computed by combining SWT with ICA is shown in Table 1 and Fig. 7, 8 and 10. The accuracy of the system is much improved, being almost 97 %. Specifically, from a total of 479 fetal heart beats, the algorithm has identified correctly 476 – true positive (TP), missed 3 – false negative (FN) and mislabeled 12 – false positive (FP). The errors appear especially due the maternal/fetal movement or due to the low SNR.

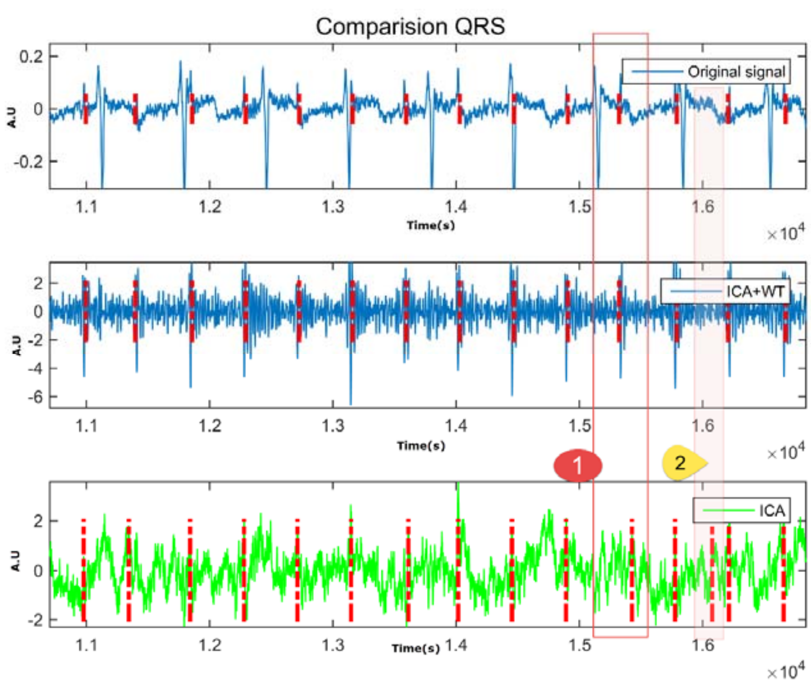

Fig. 9 Example of a False Negative(1) and a False Positive(2) QRS detection in the case of using just ICA

6. Conclusions

An improved fetal QRS detection method is proposed, that works also under high noise levels conditions. SWT was used in order to filter most of the noise components, thus the user does not have to identify the best filter for each type of noise found in the data recording. This is especially useful for automatic HR detectors where the user input should be optional. The complex shapes of the wavelets offer improved results when looking for complicated signals like fECG. The SWT application represents an interesting approach for ICA processing, highly improving the SNR and enabling the morphological analysis of the fECG. The shift-invariance recommends it for ADS processing as it does not affect the output signals.

Further study will investigate the noise level for which the proposed algorithm provide still acceptable results. A synthetic ADS generator can also be used to better control the noise and to extend the quantitative evaluation the algorithm.

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