Non-Adaptive Methods of Fetal ECG Signal Processing

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Abstract. *Abdominal fetal ElectroCardioGrams (fECGs) carry a wealth of information about the fetus including fetal Heart Rate (fHR) and signal morphology during different stages of pregnancy. Here we report our results on the implementation and evaluation of two non-adaptive signal processing methods suitable for fECG signal extraction, namely: the Independent Component Analysis (ICA) and the Principal Component Analysis (PCA) Methods. We used the fetal heart rate extracted from fECG signals (in Beats Per Minute - BPM) and Signal-to-Noise Ratio (SNR) as effective performance evaluation metrics for our applied methods. Our findings demonstrated that given adequate SNR, these methods produced excellent results in accurate determination of fHR. Furthermore, we found out that compared to the PCA Method, the ICA Method produces a lower variance in the detection of the fHR.*

Keywords

Blind source separation, ECG extraction, fetal ElectroCardioGram (ECG), independent component analysis, non-adaptive filtration, non-invasive fetal monitoring, principal component analysis.

1. Introduction

ElectroCardioGraphy (ECG) is a diagnostic method which detects the electrical activity of the cardiac muscle. In clinical practice, ECG is utilised to diagnose heart arrhythmia, ischemia, and to assess the efficiency of the treatment with drugs. For fetal monitoring, fetal ElectroCardioGraphy (fECG) can be used. From the fECG, it is possible to determine fetal Heart Rate (fHR), which can provide information about fetal hypoxia [1]. Fetal ECG contains potentially valuable information that could not be acquired by conventional ultrasound-based methods [33], [34] and [35]. The methods for fECG measuring can be invasive or non-invasive. Invasive method is the most accurate method for measuring fHR and is performed by direct transvaginal Fetal Scalp Electrode (FSE) attached directly to the fetus. Nevertheless, it is dangerous and inconvenient for both mother and fetus due to its invasive nature [2]. For these reasons, invasive method is being replaced by non-invasive method, which is measured by means of electrodes placed on maternal abdomen. This signal (abdominal ECG, aECG) contains both maternal and fetal component and also some noise caused by maternal and fetal muscle activity, potentials generated by respiration and stomach, noise generated from electrode-skin contact, etc. Equation (1) illustrated the above mentioned relations, where x_{aECG} is aECG,

x_{mECG} is materal ECG (mECG), x_{fECG} is fECG, and n is noise [9]:

$$x_{\mathrm{aECG}}(n) = x_{\mathrm{mECG}}(n) + x_{\mathrm{fECG}}(n) + n(n). \quad (1)$$

The value of Signal to Noise Ratio (SNR) depends on the abdominal electrodes placement [4] and [32] gestational age, and fetal position [2]. The placement of the electrodes is not standardized making it difficult to automate the fHR measurement [4]. Normal fetal Heart Rate (fHR) usually ranges from 120 to 160 Beats Per Minute (BPM) compared to maternal heart rate, which ranges from 70 to 80 BPM [3]. In addition, maternal signal amplitude significantly differs from the fetal signal amplitude, which is 10 to 30 times weaker. Although there is no direct neural connection between mother and the fetus, hormones and placenta can affect fHR and fetal blood pressure. Figure 1 shows that the blood circulation in the fetus varies from the circulation of a newborn and adult person.

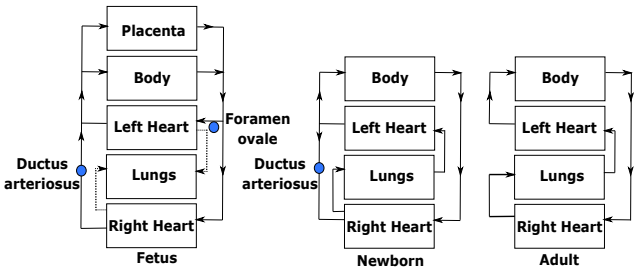


Fig. 1: Circulation of fetus, newborn and adult person.

Non-invasive measurement of fECG is performed by means of a single-channel or multichannel source signals [2]. These signals are processed by using the adaptive and non-adaptive methods. Although several techniques and fECG extraction algorithms have been tested, an optimal solution has not been found yet.

1.1. Adaptive Methods

Adaptive methods are characterized by an ability to automatically set its coefficients according to varying circumstances. Adaptive algorithms use aECG as the primary output, whereas the signal recorded on the maternal thorax (mECG) is used as the reference input due to the fact that it is considered to contain only the maternal component. Non-linear adaptive techniques include Artificial Neural Networks (ANN), methods using a Hybrid Neural Network (HNN), and apply the techniques of Adaptive Neuro-fuzzy Inference System (ANFIS) [2] and [5]. Linear adaptive methods include the methods based on the theory of Kalman filtering (KF), Least Mean Squares algorithm (LMS) [6], Recursive Least Squares algorithm (RLS) [7], and methods based on Adaptive Linear Neuron (ADALINE) [2].

1.2. Non-Adaptive Methods

This paper is mainly focused on the non-adaptive methods, which can be used for the elimination of the unwanted signal and for fECG signal extraction without any adaptation of the system. Figure 2 shows different non-adaptive methods using multichannel or single channel signal sources.

1) Single Channel Signal Source

Many non-adaptive methods use the Single channel signal source, e.g. methods based on Wavelet Transform (WT), Complex Wavelet Transform (CWT) [8], Pitch Synchronous Wavelet Transform (PSWT) [11] or Discrete Wavelet Transform (DWT) [9] and [10]. Hassanpour et al., 2006 [9] and Bhoker et al. 2013 [10], tested the DWT for fECG extraction. The results showed that this method is able to correctly detect R-R interval.

Karvounis et al., 2004 [8], tested CWT, which is used for automatic fECG extraction from aECG. They found out that this algorithm is very fast and accurate and could be used for simultaneous monitoring of fECG and mECG in order to obtain mHR. Kumar et al., 2016 [11], evaluated PSWT and they reached better SNR and correct estimation of fHR. Another non-adaptive method, Correlation Technique (CT), was introduced by Bemmel et al., 1968 [12]. However, this method is not suitable for estimating fECG. Levkov et al., 2005 [9], introduced Subtraction Technique (ST) and suggested that method does not defect spectrum of the fECG during elimination of network disturbance when compared to the other methods. Hon et al., 1964 [14], improved SNR ranging from 10 to 20 dB during fECG estimation by using Averaging Technique (AT).

Su et al., 2016 [15], dealed with nonlinear time-frequency analysis called De-shape Short-time Fourier Transform (STFT) and non-local median method and concluded that these methods have better performance than adaptive methods. These methods can estimate fECG even if aECG contains more noise and provide more information included in single aECG such as nonlinear relationships between consecutive cardiac activities.

Lee et al., 2016 [16], investigated the method of Sequential Total Variation Denoising (STVD) and demonstrated that fECG can be obtained with lower errors and it is feasible for real time fHR monitoring in the future. Tan et al., 2015 [17], introduced Fuzzy C-means Clustering Method (FCM) and their results showed that the method is extremely effective and safe in the monitoring during the pregnancy and it is very simple and suitable method for monitoring multiple fetuses in the womb.

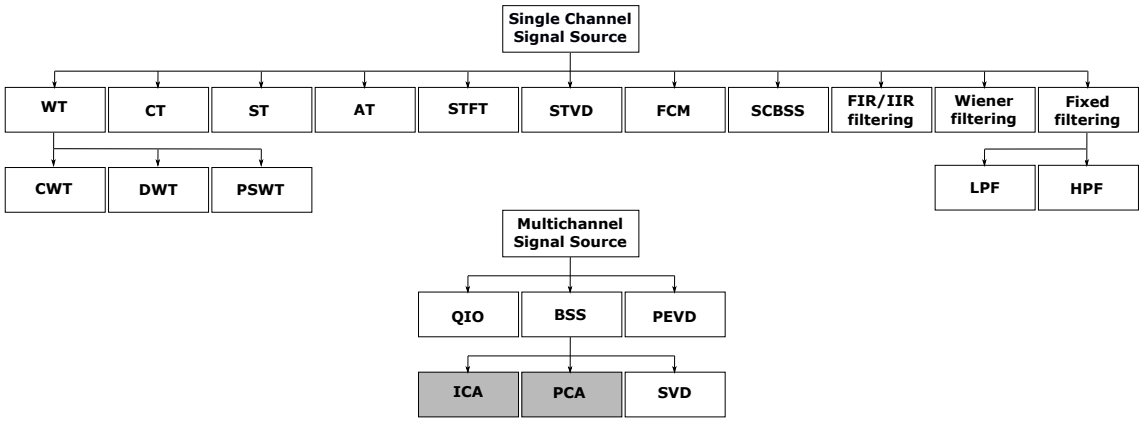


Fig. 2: Non-adaptive methods.

Peng Ju He et al., 2016 [18], focused on a Single Channel Blind Source Separation (SCBSS) and proved that this method is able to detect fHR in case of multiple pregnancy. Additionally, this method is able to extract fECG from aECG. Non-adaptive methods also include regression techniques, frequency selective filters with Finite Impulse Response (FIR) and Infinite Impulse Response (IIR), methods based on Wiener filtering theory and fix filtering, which includes Low-Pass Filter (LPF) and High-Pass Filter (HPF) [2].

2) Multichannel Signal Sources

Multichannel signal sources are used mainly for the implementation of the methods based on Blind Source Separation (BSS). These methods include Independent Component Analysis (ICA), Principal Component Analysis (PCA), and Singular Value Decomposition (SVD). Raj et al., 2015 [19], proposed Fast ICA algorithm for fECG extraction and the results showed that this method has very good performance. It is the most commonly used method, for more information, please see [20], [21] and [28]. Bacharakis et al. [22], focused on the use of PCA and proved that this method has good results but ICA method shows better performance. ICA and PCA, the main methods tested in this paper, will be explained in more detail in Sec. 2. For more information about PCA, see [29].

Leach et al. [23], discussed about SVD method and concluded that this method is very effective for fECG extraction and noise filtering. Unfortunately, the algorithm is computationally demanding. Varanini et al., 2016 [24], introduced the method of Quality Index Optimization (QIO) and concluded that this method can be used even if the fECG has a low amplitude. Kumar et al., 2016 [11], used the combination of SVD method and polynomial classifiers. The results showed that this combination improves SNR than when using SVD method alone.

Gao et al., 2003 [21], tested the combination of SVD and ICA methods and found out that this combination can be used, when mECG and fECG are overlapped. Liu et al., 2015 [25], proposed a novel integrated algorithm based on ICA, Ensemble Empirical Mode Decomposition (EEMD) and Wavelet Shrinkage (WS). They concluded that the tested combination improves SNR, correlation coefficient (R), and Mean Squared Error (MSE).

Ayat et al., 2015 [26], introduced the combination of polynomial networks and Savitzky-Golay smoothing filters. The results proved that this combination provides better performance and can be use in real-time fECG monitoring. Redif et al., 2016 [27], discussed the method using Polynomial Matrix Eigenvalue Decomposition (PEVD). According to the results, this method is not accurate in detetecting P and T waves. On the other hand, in the detection of the R waves the method has proven itself.

3) Steps of This Work

Based on the extensive research of the literature discussed above, we chose ICA and PCA methods. Moreover, according to our initial testing, they provided the best results. In this paper, Sec. 2. deals with the algorithms of ICA and PCA methods, describes generator of synthetic data, and the parameters used to evaluate the quality of the experiments. In Sec. 3. we introduce the results which are then discussed in Sec. 4.

2. Methods

2.1. ICA

Independent Component Analysis is the most performed method of non-adaptive methods using mul-

tichannel signal sources. It is a method for finding hidden vectors in the data file [21]. ICA estimates the fECG signal from the signal mixture. ICA intends to find non-Gaussian data with independent components, which are statistically independent, or at least almost statistically independent. Statistical independency means that information contained in one variable does not provide information about another one. One limitation of this method is that the signals in abdominal mixture overlap. In addition, this method requires at least two abdominal electrodes to record the input signals.The Algorithm is very quick and effective in extracting fECG.

The principle of ICA can be described simply as a room with two persons that are communicating. In this room, there are also two microphones located at different places providing two signals $x_1(t)$ and $x_2(t)$, where x_1 and x_2 are amplitudes and t denotes the time. Each signal is a sum of speech signals and marked as $s_1(t)$ and $s_2(t)$. This problem, when two or more people are talking, is a so-called cocktail-party problem [28]. In case of fetal monitoring, the maternal and fetal components in the abdominal signals are considered as the two voices in the previous example. Thus, ICA is an ideal method for extracting fECG. The principle is described by Eq. (2) and Eq. (3), where a_{11}, a_{12}, a_{21} and a_{22} are parameters depending on distance of a speaker from a microphone:

$$x_1(t) = a_{11}s_1 + a_{12}s_2, \tag{2}$$

$$x_2(t) = a_{21}s_1 + a_{22}s_2. \tag{3}$$

A problem is that the parameters a_{ij} are unknown. The solution is to assume that $s_1(t)$ and $s_2(t)$ are statistically independent (it is true in many cases). That allows to separate the original signals from the abdominal mixture [28]. For ICA, linear signals x_1 to x_n from n independent components are defined by Eq. (4):

$$x_j = a_{j1}s_1 + a_{j2}s_2 + \cdots + a_{jn}s_n. \tag{4}$$

Time index t is obtained and then every mixture of signals and every independent component s_k are random variables. In addition, it is assumed that mixture of signals and independent components have a zero mean value. If not, observed variables x_i can be always centered by subtracting mean of the samples, thus creating a zero mean model. It is very beneficial to use vector-matrix notation instead of the sum. Then matrix $\mathbf{A}_{mix}$ is used with elements a_{ij} as it is shown in Eq. (5), which has rows with transposed vectors $\vec{x}^{\mathrm{T}}$ [28]:

$$\vec{x} = \mathbf{A}_{mix} \cdot \vec{s}. \tag{5}$$

Sometimes, the columns of matrix $\mathbf{A}_{mix}$ are needed and for this reason, Eq. (5) is modified by model a_j and then we obtain Eq. (6). If we assume that components are statistically independent and have non-Gaussian distribution, it is possible to assume that mixture matrix is square and can be calculated with its inverse matrix $\mathbf{W}$ for estimation of matrix $\mathbf{A}_{mix}$, [28]. Then independent components are obtained from this matrix as in Eq. (7):

$$\vec{x} = \sum_{i=1}^{n} a_i \cdot s_i, \tag{6}$$

$$\vec{s} = \mathbf{W} \cdot \vec{x}. \tag{7}$$

Fast ICA algorithm is divided into 6 steps [20]. First, given mixed signals are converted into other signals such that covariance matrix $\mathbf{B}$ computed using the converted signals is the identity matrix. Then initialize values for the matrix $\mathbf{B}$ to achieve $\mathbf{B}^{\mathrm{T}}\mathbf{B} = 1$. Third step is updating elements of the matrix $\mathbf{B}$ using iteration formula (update all elements of this matrix). In step four, columns of matrix $\mathbf{B}$ are orthonormalized. Fifth step is repeating step three and four for each iteration. Finally, the component is obtained by multiplying $\mathbf{B}^{\mathrm{T}}$.

It is necessary to do pre-processing of signal by centering and whitening before applying ICA algorithm. Centering creates a vector with zero mean value and then whitening creates a vector which is white, its components are uncorrelated and their variances equal unity. Figure 3 shows block diagram of ICA. For more information about ICA and FastICA, please see [20], [21] and [28].

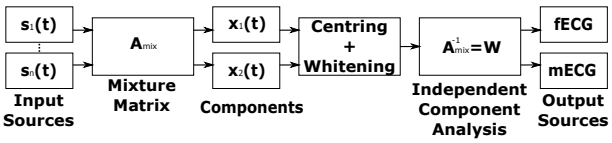


Fig. 3: Block scheme of independent component analysis.

2.2. PCA

Principal component analysis replaces original variables, which are correlated, with principal components that are uncorrelated and in the most cases are linear combination of original variables. Input of PCA is the matrix $\mathbf{X}$, which contains n samples for p original variables. Output of PCA is the matrix $\mathbf{Z}$, which contains n samples, but for p principal variables [29]. When assuming that matrix $\mathbf{X}$ is centered by columns, which indicates that means of columns of matrix $\mathbf{X}$ equals to zero, then matrix $\mathbf{Z}$ contains columns of principal components created by linear combination of columns of matrix $\mathbf{X}$. This applies for Eq. (8), where $\mathbf{A}$ the orthogonal (uncorrelated) matrix and its inverse transformation is defined by Eq. (9):

$$\mathbf{Z} = \mathbf{X} \cdot \mathbf{A}, \tag{8}$$

$$\mathbf{X} = \mathbf{Z} \cdot \mathbf{A}^{\mathrm{T}}. \tag{9}$$

From Eq. (8) and Eq. (9) following equality $\mathbf{X} \cdot \mathbf{X}^{\mathrm{T}} = \mathbf{Z} \cdot \mathbf{Z}^{\mathrm{T}}$ can be defined. It indicates that both coordinate systems have the same Euclidean distance between the points and have the same angle between the vectors connecting points and coordinate origin. Matrix $\mathbf{G}$ is created because matrix $\mathbf{A}$ causes rotation around coordinate origin [29]. This new matrix $\mathbf{G}$ causes rotation around coordinate origin and for this matrix, principal components are orthogonal as in Eq. (10):

$$\mathbf{Z} = \mathbf{X} \cdot \mathbf{G}. \tag{10}$$

Statistically, PCA is identified as multivariate method, which is based on the decomposition of the covariance matrix. For analysis, PCA ussually uses two or three components. These components are graphically displayed in the space, which provides easy detection of structures, such as a group of points. To estimate structures, different two or three principal components can be used and take PCA as the projection of 2D or 3D data. Usually, chart of columns from columns of matrix $\mathbf{Z}$ is created. It is influenced by the transformation of the data.

There are several limitations of PCA procedure. Some components, the variablility of which is low, are important for analysis of multivariate data. It is difficult to assess which part of variability of data is unimportant [29].

Four steps are given in PCA data analysis: transformation of the data, distribution of covariance or correlation matrix, determination of the number of relevant principal components, and graphical representation of multivariate data [29].

Sometimes it is difficult to determine number of relevant principal components. For purposes of ECG signal processing, we will use two components to separate mECG and fECG. Graphical representation is performed for the specific pairs of principal components. It usually adds vectors of projections as rows of matrix $\mathbf{P} = \mathbf{G} \cdot \mathbf{L}$ that create combination chart.

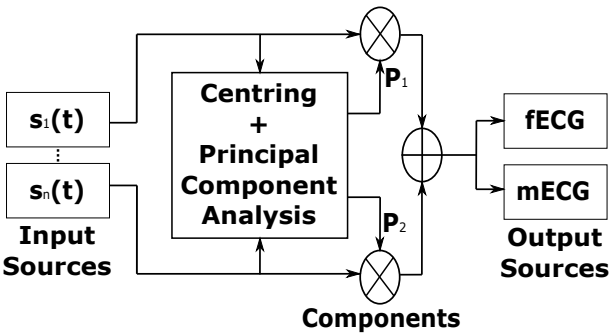


Fig. 4: Block scheme of principal component analysis.

Equation (11) shows that basis of PCA method is the spectral decomposition of covariance matrix on eigenvalues and vectors. This method uses SVD method directly as in Eq. (11) [29]. Mostly, shortened form of the SVD method, which has variables $\mathbf{U}$ and $\mathbf{S}$ with changed dimensions, is used and PCA method is calculated by Eq. (12):

$$\mathbf{Y} = \mathbf{U} \cdot \mathbf{S} \cdot \mathbf{V}^{\mathrm{T}}, \tag{11}$$

$$\mathbf{Z} = \mathbf{U} \cdot \mathbf{S}. \tag{12}$$

It is necessary to do pre-processing of the signal only by centering. Centering creates a vector with zero mean value, similarly as in case of ICA algorithm, but whitening is not usually necessary. In Fig. 4, we can see block diagram of PCA. More information about PCA can be found in [22] and [29].

2.3. Dataset

For the experiments, synthetic data were used. The data were created by the signal generator introduced by Martinek et al., 2016 [30]. It is a multi-channel generator which allows for the creation of synthetic signals nearly identical to the real signals. The biggest advantage of this generator is that it provides a reference fECG and mECG for the selected electrodes (abdominal or thoracic). Reference fECG is used to check the accuracy of proposed methods. This generator can determine fHR, mHR, interference, gestational age, or simulate the hypoxic conditions during 20th to 42nd week of pregnancy. Another advantage of this generator is the possibility to generate the signal by setting properties for six leads, four of them are abdominal and two of them are thoracic.

Figure 5 shows 5 abdominal electrodes, which were chosen for estimation in this work because they provide ideal position for evaluation. Non-adaptive methods require at least two abdominal electrodes and do not use thoracic electrodes. Using the generator, we set fHR on value 130, mHR on value 75, and recording time of data on 30 seconds. Records of aECG data from these 5 electrodes are generated for different levels of input signals in range from −5 dB to −50 dB. From these 5 abdominal electrodes, we get 10 combinations by using two of them, 10 combinations by using three of them, 5 combinations by using four of them and 1 combination by using all of them. That is in total 26 combinations for evaluation of proposed methods as we can see in the first columns of all tables in Sec 3.

2.4. Evaluation Parameters

Evaluation of extracted fECG by proposed methods can be performed subjectively or objectively. Subjec-

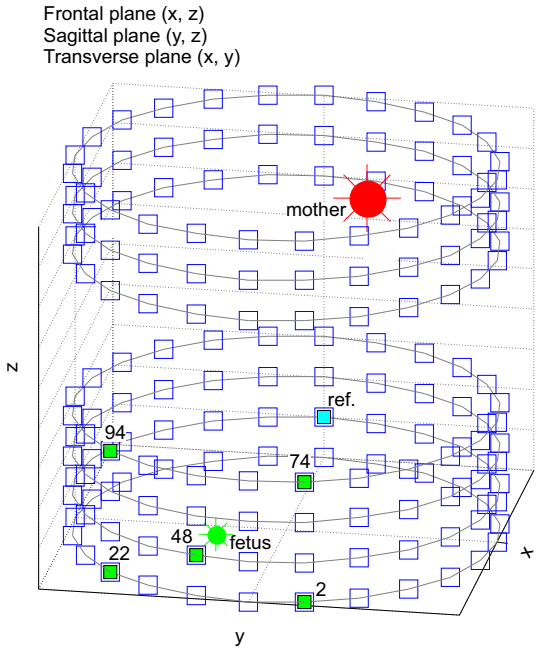


Fig. 5: Chosen abdominal signals from generator.

tively, we can evaluate the graph of extracted fECG and evaluate if this fECG is similar to ideal form fECG visually. For this work, objective evaluation, using parameters such as BPM and SNR, is more relevant.

Evaluation by using SNR is used to define the relationship between the useful signal and the noise. The resulting SNR is calculated by subtracting input SNR (SNR_{in}) from output SNR (SNR_{out}). If SNR_{in} and SNR_{out} is known, we can calculate resulting SNR and use it for the evaluation of the filtering by using proposed non-adaptive method. In Eq. (13), we can see calculation of SNR_{in} and in Eq. (14) we can see calculation of SNR_{out}, where $fECG_{ideal}$ is generated fECG by generator, $aECG_{input}$ is aECG which contains maternal and fetal component, and $fECG_{extract}$ is the extracted fECG by proposed non-adaptive methods. We need to note that $aECG_{input}$ contains mECG and fECG, so in Eq. (13) it is necessary to subtract $fECG_{ideal}$ from $aECG_{input}$ in the denominator. Similarly, it is necessary to subtract $fECG_{ideal}$ from $fECG_{extract}$ in Eq. (14):

$$SNR_{in} = 10\log_{10}\frac{\sum_{n=1}^{N-1}(fECG_{ideal})^2}{\sum_{n=1}^{N-1}(fECG_{input}-fECG_{ideal})^2}, \quad (13)$$

$$SNR_{out} = 10\log_{10}\frac{\sum_{n=1}^{N-1}(fECG_{ideal})^2}{\sum_{n=1}^{N-1}(fECG_{extract}-fECG_{ideal})^2}. \quad (14)$$

Heart rate is a very important evaluation parameter. To detect more accurate fHR, the algorithm does not use fix amplitude level. In this work, the number of BPM in a recording is solved by using Detector of R waves. We used full implementation of the Pan-Tompkins filter [31].

3. Results

This section will be mainly focused on evaluation ICA and PCA by BPM, fHR, and mHR, respectively. Next, evaluation by using SNR is only implemented for PCA, since ICA change the amplitude of obtained fECG as we can see in Fig. 9 and Fig. 10. Therefore, it is impossible to calculate SNR.

3.1. Heart Rate (HR)

As it was mentioned before, this paper is mainly focused on fHR determination. In Tab. 2 and Tab. 3, we can see results of fHR determination for ICA and PCA. First columns of these tables show 26 combinations of electrodes. All these combinations use signals with different input quality levels. Input quality levels of signals are marked by Roman numerals from I to X and the values of these signals for each electrode on a certain level are included in the Tab. 1.

1) Determination of fHR by Using ICA

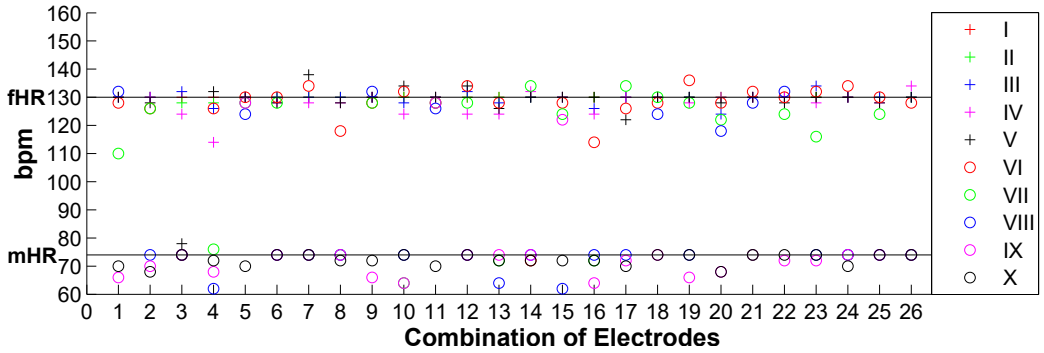
The left part of Tab. 2 shows results of determination of fHR by ICA from extracted fECG. In this part, we can see that ICA is good in detection fHR for the most cases in range of quality level of input signals from I to VI. In quality level of input signals VII, this method is not that effective. In last three quality levels, there is the obtained HR of maternal component (mHR).

In the right part of Tab. 2, we can see that determination of mHR from extracted component mECG is good for the most quality levels of input signals.

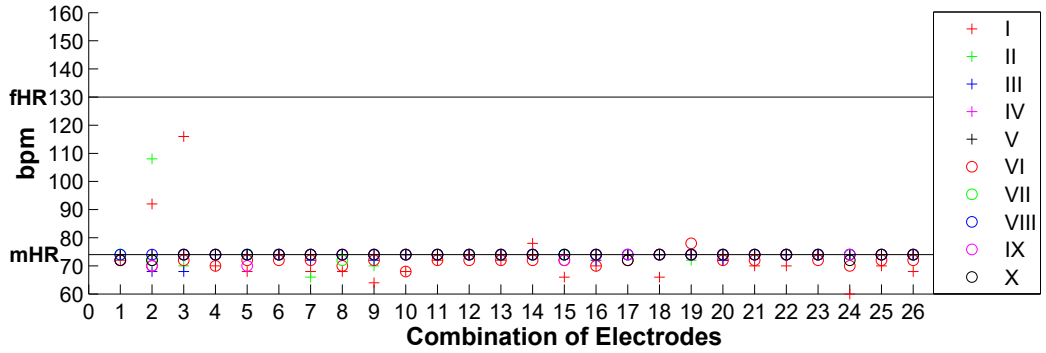
Results from Tab. 2 are also shown in Fig. 6. We can see the most of combinations by using ICA have approximately same value of fHR as ideal (reference) fECG. Figure 6(a) shows detection of fHR in extracted fECG. Blue, pink, and black circles represent quality levels from VIII to X, have mainly different fHR than ideal form of fECG. Figure 6(b) shows detection of mHR in extracted mECG. Lines in both parts of Fig. 6 represent generated HR value which was 130 for fECG and 75 for mECG.

2) Determination of BPM by Using PCA

Again, in left part of Tab. 3 we can see determination of fHR from extracted fECG but by using PCA. In



(a) Determination of BPM in extracted fECG.



(b) Determination of BPM in extracted mECG.

Fig. 6: Recorded detection accuracy of fHR and mHR by using ICA.

Tab. 1: Table of SNR_{in} for different quality levels.

Electrode	SNR_{in}									
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**
2	4.1	-3.1	-6.9	-13.2	-16.8	-21.4	-30.0	-32.6	-37.8	-41.5
22	6.8	-0.2	-4.0	-10.2	-14.0	-18.6	-26.2	-29.9	-35.0	-38.7
48	10.1	2.6	-1.1	-7.2	-10.7	-15.2	-22.9	-26.9	-31.4	-35.6
74	0.7	-6.7	-10.4	-16.7	-20.1	-24.6	-32.2	-36.0	-41.0	-44.9
94	-0.2	-7.0	-11.0	-17.1	-20.9	-25.7	-33.1	-36.7	-42.1	-45.6

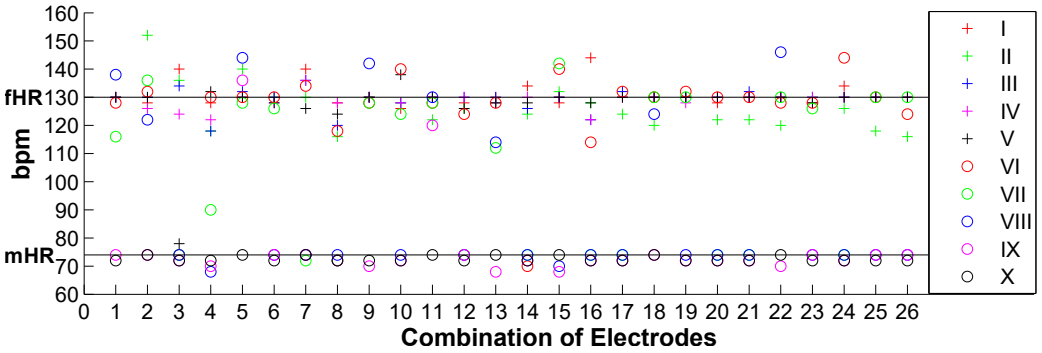
this left part, a good detection of fHR also prevails. So again, method of blind source separation proves to be effective in fHR determination for the most quality levels of input signals from I to VI. In quality level VII, this method is not so effective and in last thee quality levels, the value of obtained HR is equal to maternal component (mHR) instead of fetal one (fHR).

In the right part of Tab. 3, same as in Tab. 2, there is determination of mHR from second extracted maternal component (mECG) by PCA. PCA is suitable for most of the quality levels of the input signals. Determination of mHR is not sufficient only in the first two quality levels due to high SNR_{in} at these levels.

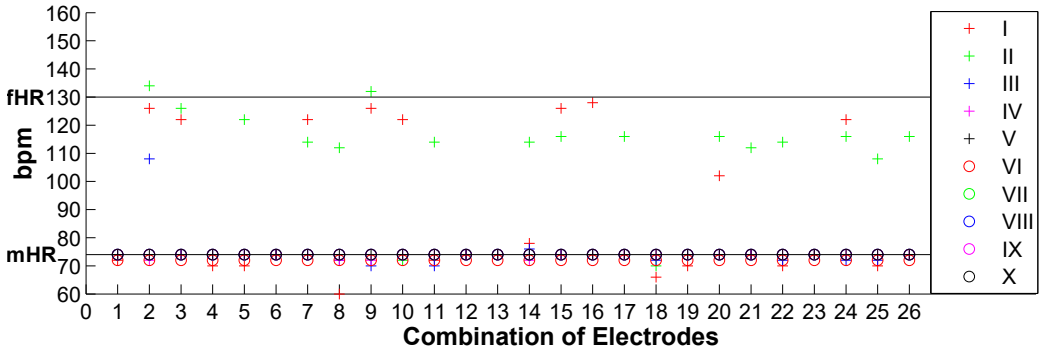
Figure 8 illustrates the results from Tab. 3. We can see that most of the combinations using PCA have fHR approximately same as the ideal (reference) fECG. Figure 8 shows detection of fHR in extracted fECG. Blue, pink, and black circles again represent quality levels from VIII to X, have mainly different fHR than the ideal fECG. Figure 7(b) shows detection of mHR in extracted mECG. Lines in both parts of Fig. 7 represent the HR set in the generator, i.e. 130 for fECG and 75 for mECG.

3) Summary of fHR and mHR Detection

As we assumed, both of the proposed methods are very accurate in detection of fHR from extracted fetal component and mHR from extracted maternal component. Both methods stop working in quality index of input signals VIII, i.e. approximately for the values of SNR_{in} in the range from -30 to -35 dB. From upper figures in Fig. 6 and Fig. 7, we can see that in case of determination of fHR, ICA shows slightly better results than PCA.



(a) Determination of BPM in extracted fECG.



(b) Determination of BPM in extracted mECG.

Fig. 7: Recorded detection accuracy of fHR and mHR by using PCA.

Tab. 2: Table of BPM detected from the extracted components by using ICA.

Combination of electrodes	Determinationof fHR by ICA									
	I	II	III	IV	V	VI	VII	VIII	IX	X
2, 22	130	130	130	130	130	128	110	132	66	70
2, 48	130	130	130	130	128	126	126	74	70	68
2, 74	130	128	132	124	78	74	74	74	74	74
2, 94	130	128	126	114	132	126	76	62	68	72
22, 48	130	130	130	130	130	130	128	124	128	70
22, 74	130	130	130	128	128	130	128	74	74	74
22, 94	130	130	130	128	138	134	74	74	74	74
48, 74	130	130	130	128	128	118	74	74	74	72
48, 94	130	130	130	130	130	128	128	132	66	72
74, 94	130	130	128	124	134	132	64	74	64	74
2, 22, 48	130	130	130	130	130	128	128	126	128	70
2, 22, 74	130	130	132	124	134	134	128	74	74	74
2, 22, 94	130	130	128	124	126	128	72	64	74	72
2, 48, 74	130	130	130	132	130	72	134	74	74	72
2, 48, 94	130	130	130	130	130	128	124	62	122	72
2, 74, 94	130	130	126	124	130	114	72	74	64	72
22, 48, 74	130	130	130	130	122	126	134	74	72	70
22, 48, 94	130	130	130	130	130	128	130	124	74	74
22, 74, 94	130	130	130	128	130	136	128	74	66	74
48, 74, 94	130	130	124	130	128	128	122	118	68	68
2, 22, 48, 74	130	130	130	130	130	132	74	128	74	74
2, 22, 48, 94	130	130	130	130	128	130	124	132	72	74
2, 22, 74, 94	130	130	134	128	130	132	116	74	72	74
2, 48, 74, 94	130	130	130	130	130	134	74	74	74	70
22, 48, 74, 94	130	130	130	128	128	130	124	74	74	74
2, 22, 48, 74, 94	130	130	130	134	130	128	74	74	74	74

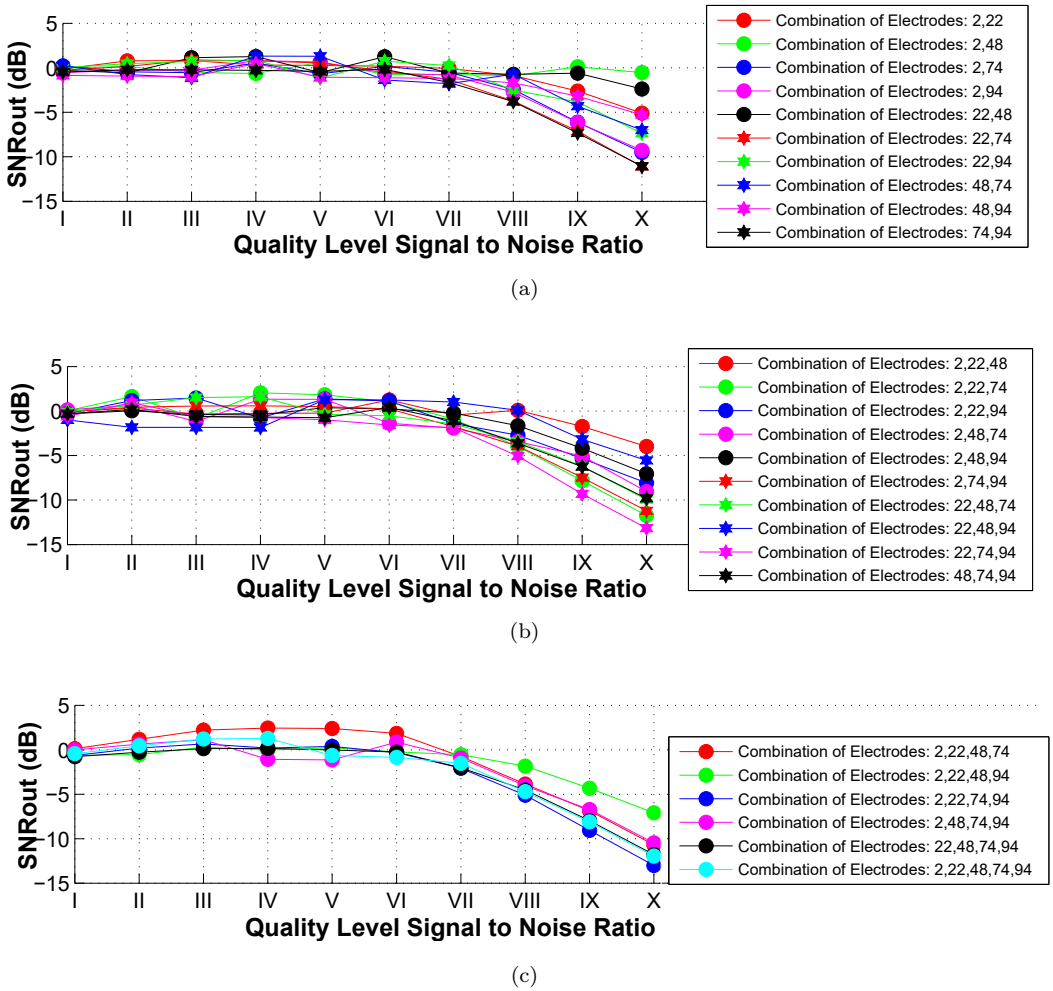


Fig. 8: Comparison of results by PCA for different combinations of electrodes. Charts SNR_{out} dependence on different quality levels of input signals.

3.2. SNR

Second part of the evaluation is focused only on PCA since ICA changes the amplitudes of both components (see in Fig. 9 and Fig. 10) and changes order of the estimated components. Similarly, as in evaluation of HR, input signals with different quality levels are used (see Tab. 1). Table 4 shows averaged values of computed SNR_{out}. It shows if method on a certain quality level of input signals still works or not. Table 4 shows average values of SNR_{out} and resulting SNR for all combinations of different quality levels of corresponding input signals after using PCA.

In this paper, only averaged values are used because the ideal fECG signals, used in dominator in Eq. (14), differ for a certain combination of electrodes. For example in case of electrodes 2 and 22, we must compute the ideal form of fECG to determine the final SNR_{out}. We get one table of SNR_{out} values just for one quality level of input signals. For these 10 quality levels of input signal, we get 10 tables for SNR_{out} and 10 tables for SNR. Then we average the values computed for one combination in certain quality level. Figure 8 shows process of all 26 combinations for all quality levels of input signals. Figure 8(a) shows the combinations of two electrodes, Fig. 8(b) shows the combinations of three electrodes and Fig. 8(c) shows the combinations of four and five electrodes. According to Fig. 8, most of the electrodes combinations stop working in the quality level of input signals ranging from VI to VII. So similarly as in previous evaluation of HR, this evaluation shows that PCA stops working with input signals in range from −30 to −35 dB and in this range, PCA improves SNR approximately up to 25 dB.

3.3. Subjective Observations

Subjective evaluation is not suitable approach, some observations are interesting, though. One of them was already mentioned and concerns ICA. This method changes amplitudes of the components as we can see

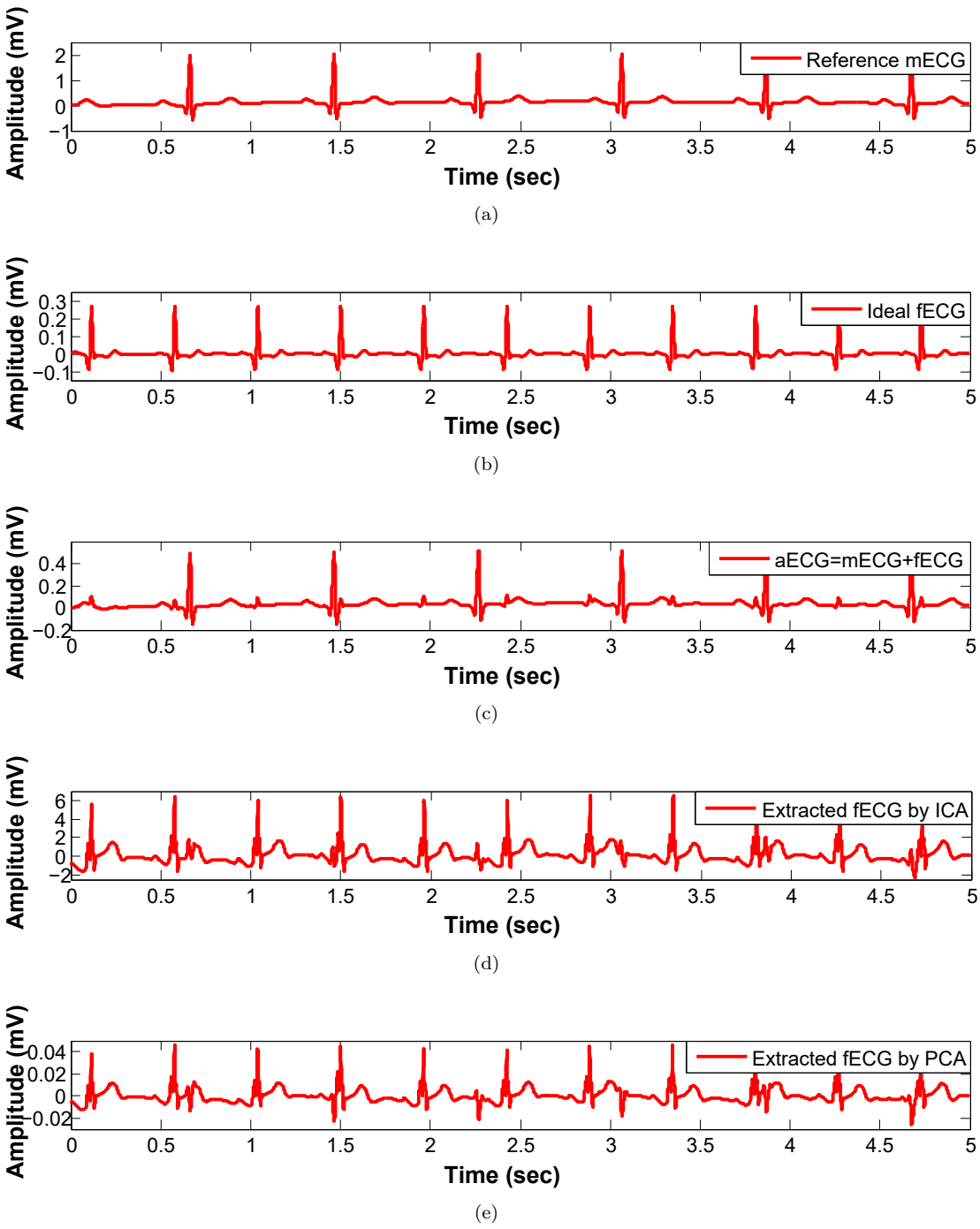
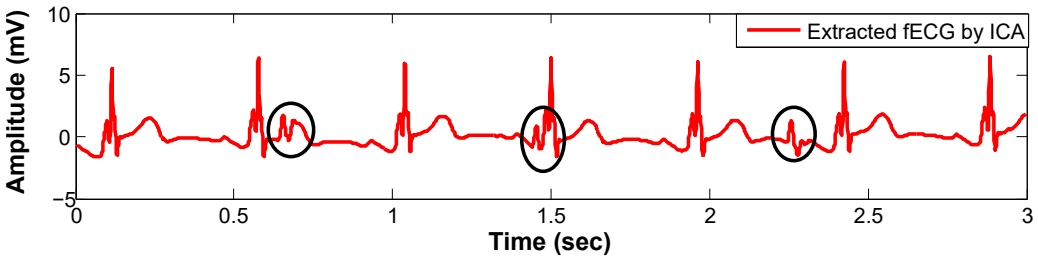
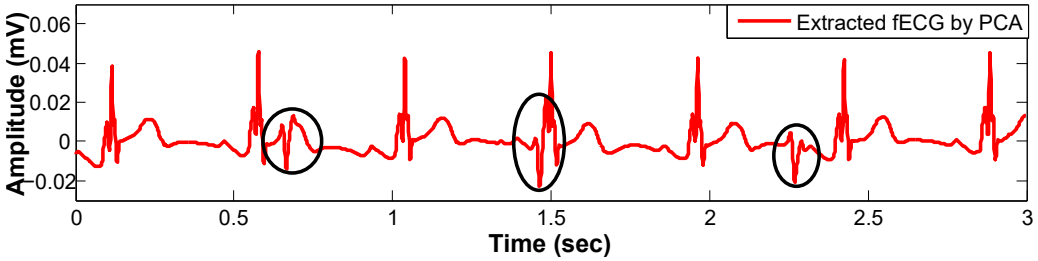


Fig. 9: ICA and PCA output for fECG estimation.

in Fig. 9 and Fig. 10, where fECG is extracted using ICA and PCA, respectively. This method also changes order of the estimated components. That is important in case of creating a program to display the extracted components. Figure 9 shows an example of fECG extraction by ICA and PCA. For the extraction, input signals with quality level V were used, which ensures the ideal accuracy for extraction of fECG. The signal in Fig. 9(a) is the generated mECG from electrode number 2. Figure 9(b) is the generated fECG from electrode number 2, Fig. 9(c) is aECG from electrode number 2. Figure 9(d) is the extracted fECG by using ICA for combination of electrodes 2 and 48. Figure 9(e) is extracted fECG by using PCA for combination of electrodes 2 and 48. We can see that mECG signal is suppressed and only a small random noise remains. In Fig. 10 we can see the deformations caused by maternal QRS complexes on both extracted fECGs by ICA and PCA. These deformations are marked by in Fig. 10.



(a)



(b)

Fig. 10: Deformations of extraction fECG signal due to mHR.

Tab. 3: Table of BPM detected from the extracted components by using PCA.

Combination of electrodes	Determinationof fHR by PCA									
	I	II	III	IV	V	VI	VII	VIII	IX	X
2, 22	130	130	130	130	130	128	116	138	74	72
2, 48	128	152	130	126	130	132	136	122	74	74
2, 74	140	136	134	124	78	74	74	74	72	72
2, 94	128	118	118	122	132	130	90	68	70	72
22, 48	130	140	132	130	130	130	128	144	136	74
22, 74	130	130	130	128	128	130	126	74	74	72
22, 94	140	130	136	136	126	134	72	74	74	74
48, 74	128	116	120	128	124	118	72	74	72	72
48, 94	130	130	130	130	130	128	128	142	70	72
74, 94	126	128	128	128	138	140	124	74	72	72
2, 22, 48	130	122	130	130	130	128	128	130	120	74
2, 22, 74	128	126	130	130	126	124	74	74	74	72
2, 22, 94	130	128	130	128	128	128	112	114	68	74
2, 48, 74	134	124	126	130	128	70	74	74	72	72
2, 48, 94	128	132	130	130	130	140	142	70	68	74
2, 74, 94	144	128	122	122	128	114	74	74	72	72
22, 48, 74	130	124	132	130	130	132	74	74	72	72
22, 48, 94	130	120	130	130	130	130	130	124	74	74
22, 74, 94	130	130	130	128	130	132	130	74	72	72
48, 74, 94	128	122	130	130	130	130	74	74	72	72
2, 22, 48, 74	130	122	132	130	130	130	74	74	72	72
2, 22, 48, 94	130	120	130	130	130	128	130	146	70	74
2, 22, 74, 94	128	130	130	130	128	128	126	74	74	72
2, 48, 74, 94	134	126	130	130	130	144	74	74	72	72
22, 48, 74, 94	130	118	130	130	130	130	130	74	74	72
2, 22, 48, 74, 94	130	116	130	130	130	124	130	74	74	72

4. Conclusion

In this paper, we have tested ICA and PCA mainly for fHR detection. Both methods showed good results, but the fHR detection using ICA showed smaller variance of values. Methods fail to work when input SNR ranges from −30 to −35 dB. In another evaluation, we used SNR as the main parameter. However, this evaluation is possible only for PCA since ICA changes amplitude of extracted components. This evaluation showed similar results-PCA had high performance besides the range from −30 to −35 dB. The extracted fECG signal was deformed in case of using both algorithms by the maternal residues. These algorithms show very high performance, therefore it is possible to use them in the

Tab. 4: Table of calculated values of SNR_{out} for different input quality levels.

Combination of electrodes	SNR_{out}									
	I	II	III	IV	V	VI	VII	VIII	IX	X
2, 22	-0.13	0.79	0.81	0.31	0.27	0.17	-0.07	-0.87	-2.63	-5.09
2, 48	-0.02	0.14	-0.53	-0.63	0.61	-0.73	-0.75	-0.88	0.10	-0.54
2, 74	0.21	-0.45	-0.55	0.53	-0.67	0.14	-0.50	-2.43	-6.12	-9.52
2, 94	-0.53	-0.29	-0.27	0.81	0.65	-0.58	-0.82	-2.74	-6.15	-9.27
22, 48	-0.29	-0.57	1.14	1.26	-0.54	1.24	-0.59	-0.74	-0.60	-2.39
22, 74	-0.27	0.14	0.88	0.78	0.54	-0.35	-1.31	-3.73	-7.13	-11.10
22, 94	0.01	0.46	0.71	0.85	-1.15	0.74	0.24	-2.50	-3.85	-7.37
48, 74	0.21	-0.75	-1.13	1.31	1.30	-1.37	-1.79	-0.72	-4.32	-7.00
48, 94	-0.85	-0.94	-0.98	0.46	-1.05	-1.12	-1.21	-1.68	-3.19	-5.29
74, 94	-0.48	-0.22	-0.25	-0.28	-0.41	-0.18	-1.65	-3.80	-7.34	-11.07
2, 22, 48	-0.06	0.32	-0.33	-0.25	-0.23	1.24	-0.46	0.08	-1.73	-3.99
2, 22, 74	0.03	1.62	-0.81	2.05	1.84	1.02	-0.92	-3.96	-7.84	-11.74
2, 22, 94	-0.29	1.18	1.46	-0.78	1.35	1.14	-1.40	-2.71	-5.33	-8.08
2, 48, 74	0.13	0.64	-1.17	1.33	1.31	-1.37	-1.92	-3.43	-5.07	-9.04
2, 48, 94	-0.32	0.03	-0.39	-0.44	0.38	0.23	-0.22	-1.66	-4.18	-7.05
2, 74, 94	-0.11	0.43	0.56	0.58	0.50	0.24	-1.74	-3.93	-7.49	-11.22
22, 48, 74	-0.08	0.65	1.51	1.61	-0.37	-0.54	-1.46	-3.40	-6.22	-9.95
22, 48, 94	-1.00	-1.84	-1.84	-1.86	1.28	1.24	1.00	0.08	-3.18	-5.55
22, 74, 94	-0.60	0.95	-0.64	-0.73	-0.98	-1.57	-1.88	-5.07	-9.32	-13.16
48, 74, 94	-0.30	0.18	-0.60	-0.67	-0.75	0.40	-1.11	-3.62	-6.26	-9.82
2, 22, 48, 74	0.13	1.17	2.21	2.45	2.39	1.84	-0.77	-3.86	-6.86	-10.69
2, 22, 48, 94	-0.65	-0.54	0.30	-0.04	0.23	-0.24	-0.56	-1.83	-4.33	-7.10
2, 22, 74, 94	-0.65	0.19	0.66	0.20	0.37	-0.33	-2.07	-5.11	-9.06	-13.01
2, 48, 74, 94	-0.02	0.64	1.12	-1.07	-1.15	0.86	-0.94	-4.06	-6.73	-10.47
22, 48, 74, 94	-0.78	-0.28	0.13	0.16	-0.03	-0.26	-2.02	-4.53	-7.98	-11.80
2, 22, 48, 74, 94	-0.45	0.44	1.21	1.28	-0.63	-0.86	-1.52	-4.71	-8.11	-11.96

clinical practice for determining fHR for diagnosing fetal hypoxia. This research may be improved by testing obtained fECG by determining so-called T/QRS ratio. However, the deformation of T wave in extracted fECG must be minimal.

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