The Influence of Gestation Age on the Performance of Adaptive Algorithms Used for Fetal ECG Signal Extraction

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Abstract. *The main aims of this paper are to study the influence of the Gestation Age (GA) on the quality of recorded abdominal ECG (aECG) signals and to evaluate the performance of the LMS and RLS adaptive signal processing algorithms in the extraction of the fetal ECG (fECG) signal component from such signals. This influence is quantified as a function of the Signal-to-Noise Ratio (SNR). Our research shows that these adaptive algorithms with optimized settings can successfully be applied to extract fECG signals from the maternal aECG signals as early as the 30th week of GA, hence addressing a limitation (37 weeks or labor) in commercially available monitoring systems. We demonstrate that before this gestational age, the SNR of the maternal aECG signal is too low for these adaptive algorithms to work effectively and produce satisfactory results.*

Keywords

ECG extraction, fetal ElectroCardioGram (ECG), gestation age, LMS and RLS algorithms, non-invasive fetal monitoring.

1. Introduction

In today's clinical practice, Electronic Fetal Monitoring (EFM) is commonly used during labor and delivery. EFM is an important tool to detect fetal hypoxia, a condition in which the fetus is deprived of an adequate supply of oxygen. With the occurrence of this condition, it becomes necessary to perform an emergency cesarean section. According to the International Federation of Gynecology and Obstetrics (FIGO) Guidelines, the main parameter for fetal hypoxia detection is the value of the fetal Heart Rate (fHR) [1].

The most widely used technology for fHR monitoring is the noninvasive Doppler Ultrasound Method because it is both simple and economical. Nevertheless, as this method employs ultrasound to detect the fetal heart rate, it is significantly influenced by fetal and maternal movement artifacts and consequently is susceptible to reliability and accuracy issues. Moreover, as this method only produces an average heart rate value, it cannot be used to monitor Beat-To-Beat (BTB) heart rate variability or perform fECG signal morphology analysis. Therefore, its utilization in long-term monitoring is questionable. Other issues include the fact that the fHR may be interpreted as the mHR (also called "Signal Ambiguity" [2]). This ambiguity could result in the false negative or false positive diagnosis of fetal hypoxia and pose a danger to the unborn child or misguide the clinical staff to initiate an unnecessary cesarean section due to the absence of reassuring fetal heart rate tracings.

Currently, fetal ElectroCardioGraphy (fECG) seems to be the most promising method to provide the necessary data for the robust detection of fetal hypoxia [3]. Although this methodology was proposed several decades ago [4] and [5], it has not been fully utilized as yet due to the limitations and challenges associated with the reliable extraction of the fetal ECG component from the maternal abdominal ECG signals [6]. The other promising methods for hypoxia detection are fetal PhonoCardioGgraphy (fPCG) and fetal MagnetoCardioGraphy (fMCG). While fECG is based on the recording of the electrical activity of the heart, the fPCG signal manifests the fetal heart's mechanical (acoustical) activities and the fMCG registers magnetic fields of the fetal heart produced as a consequence of its electrical activity [7], [8], [9] and [10]. As the physical principles used in these monitoring techniques differ from the one used in the ultrasonic method, the quality of the measured signal (biopotential on the maternal abdomen) is not affected by the amount of adipose tissue (body fat) present. In addition, fetal electrocardiography is the only technique that offers realistic long-term ambulatory fHR monitoring capability. Unfortunately, the disadvantage of this noninvasive method is that it only provides information about the fetal Heart Rate (fHR) and not its signal morphology (as opposed to its invasive alternative). This limitation is mainly due to the fact that the desired (fECG) signal is relatively weak (small in amplitude) when compared with stronger signals generated by the surrounding influences in the maternal abdomen.

The invasive fECG signal recording involves performing direct measurements from the unborn fetus' head by well-trained medical specialists during later stages of labor and delivery (using a scalp electrode inserted transvaginally). Even though accurate and more informative, this method is unpleasant for the pregnant woman and creates an increased risk of maternal/fetal infection. In contrast, the noninvasively recorded aECG signal provides an indirect and less accurate measurement of its fECG signal component, as the aECG signal is formed by the superimposition of different biopotentials on the fECG signal during its propagation from the fetus' heart to the maternal abdominal electrodes. The major (strongest) component of the aECG signal, the maternal ECG (mECG) signal, produced by the maternal heart, overlaps with the fECG signal not only in time but also in the frequency domain. Its biosource (maternal heart) is large compared to the fetal heart and consequently the signal of the former has a much higher amplitude than the desired fECG signal, which is hardly noticeable in the abdominal recordings. Therefore, its filtering (extraction) requires advanced signal processing techniques. Due to the overlap of these signals in both time and frequency domains, the extraction of fECG from aECG signals is a very difficult filtering task and it has been shown that classical linear FIR filters could not work effectively in this application. Consequently, we decided to use adaptive techniques for this purpose.

In clinical practice, there are situations in which the fetal heart rate tracings may be misleading [1]. Even though adaptive signal processing algorithms have been used in some commercially available devices [11], they are mainly designed for women who are at term (at the end of 37^{th} gestation weeks or in labor). Recognizing this commercial limitation, we aim to show in the following section that adaptive signal processing algorithms, once properly designed and implemented, offer the potential to be effectively used to extract fECG signals at an earlier gestational age.

In addition to signal processing challenges, one of the major obstacles in fetal ECG signal processing is the insufficiency of available standardized and objective data during different stages of pregnancy to be used to evaluate the efficacy of these advanced algorithms. For research in conventional ECG signal processing, researchers have access to the so-called "gold-standard databases" [12] which include a large amount of recorded ECG data that follow established standards such as: the number of channels, electrode placement, sampling frequency, annotations, and so on. Nevertheless, there is no such database for fECG signals. There are some publically available data (for example [13]), but, compared to the standardized databases mentioned above, they are insufficient. These scattered and non-standardized data, acquired during different stages of pregnancy, are for different electrode placements and fetal positions. Furthermore, pathological (hypoxic) records are, understandably, almost totally nonexistent because when fetal hypoxia is detected during labor, the pregnancy must immediately be terminated by performing the cesarean section, which offers no opportunity for data collection.

To address the abovementioned obstacles, as other researchers [14] and [15] in this field have done, we recognized that an essential part of our research should be comprised of creating a synthetic data generator allowing us to generate (simulate) not only physiological but also pathological maternal and fetal ECG signals with different types of technical and biological noise added to the recorded aECG signals [16] and [17]. In addition to the generation of realistic synthetic data for signal processing experiments, the novel generator would facilitate the evaluation of the quality and efficacy of our

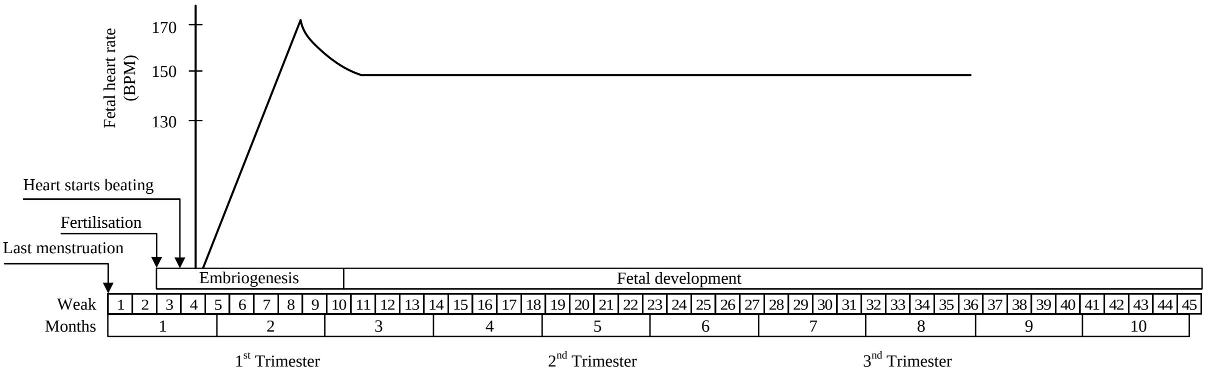

Fig. 1: The fetal development process.

algorithms in fECG signal filtering by providing reference ECG signals. It is important to emphasize that using real signals for this purpose requires recording the reference fetal signals, which only become possible during labor and delivery, by using a Fetal Scalp Electrode (FSE). Therefore, it is evident that the objective evaluation of fECG signal extraction and the subsequent optimization of the adaptive filters are critically dependent on the availability of accurate reference signals. In summary, by using our novel signal generator, it becomes possible to test, evaluate, and optimize the performance of adaptive signal processing algorithms during any stage of pregnancy because the generator provides maximal flexibility in not only allowing us to set the gestation age but also in adjusting all the generated signal properties.

2. Fetal Development

The length of pregnancy is expressed in terms of the Gestation Age (GA), which is "the number of weeks that a baby has been in the uterus." Its origin is calculated by using the date of the last normal menstrual period experienced by the mother. At first, the fetal heart has a very simple tubular structure. During the early gestational weeks, a significant development of the fetal heart leads to an increase in its size and physiological performance. At the end of the seventh week of pregnancy, the fetal heart transforms into a four-chambered organ [18]. It is well established that gestation age influences the strength of the fECG signal in a significant way. Figure 1 illustrates the influence of gestation age on fetal heart rate and the fetal heart's growth associated with an increase in the fECG signal amplitude. Twenty-one days after conception, the fetal heart starts beating. At this stage, the fetal heart rate is about 75–80 beats per minute (BPM). Afterwards, the fetal heart rate increases linearly up to about the 8th weeks of GA when it reaches its peak, varying between 165 to 185 BPM. Within weeks, the fHR exponentially decreases to a range between 150 to 25 BPM and then it stabilizes [18].

3. Methodology

In this paper, we focus on the application of two popular adaptive filtering methods and their optimization in addressing the fECG signal processing problem. Even though these algorithms have an established track record in effective fECG signal processing, their disadvantage is that they require additional electrodes to be placed on the maternal thorax or shoulder to provide the reference maternal ECG signal. This reference signal can also be estimated from linearly independent abdominal leads to eliminate the need for extra electrodes. However, for more precise results, it is recommended to use the reference maternal signal recorded directly [19]. This approach also helps to minimize the risk of signal ambiguity, which is the phenomenon whereby the fetal monitoring system mistakenly detects the mHR instead of the fHR [1].

The adaptive filter coefficients are adjusted automatically on the basis of an optimization algorithm. Adaptive methods can be linear or nonlinear. Linear adaptive filters used for fECG extraction include those using the Least Mean Squares (LMS) [20], [21], [22], [23] and [24] and Recursive Least Squares (RLS) [25] Algorithms, as well as the Comb Filter [26], Adaptive Voltera Filter [27], and Adaptive Linear Networks (ADALINE) [28]. Nonlinear techniques are those based on Artificial Intelligence (AI) and include Fuzzy Inference Systems [29], Genetic Algorithms, and Bayesian Adaptive Filtering Frameworks [30].

The adaptive methods mentioned above differ from one another. However, they all have one thing in common: the need for setting their control parameters, which is a challenging task. The optimal value of these settings is based on many factors such as the fetal position, electrode placement, stage of the pregnancy, and so on. Moreover, these setting are unique for each patient and they change during the pregnancy. Therefore, it is important to pay special attention to this aspect of adaptive filtering to achieve good results [30].

The continuous processing of both the abdominal (mECG and fECG) and thoracic (considered to maternal) ECG signals is a promising method for fHR monitoring as it is technically feasible and offers the potential benefit for accurate diagnosis of fetal hypoxia. A crucial part of this signal processing effort is the need for an adaptive system that allows for the extraction of the fECG signal component from a variety of undesired signals (including mECG). Such filtered fECG signal can then be used for diagnostic purposes (ST segment, T/QRS, and other morphological analyses). In this paper, we designed and tested an adaptive system using the LMS and RLS Algorithms for fHR detection. These methods are described in the following subsections. However, we intend to use and compare the utility of the other methods mentioned above in our future research.

3.1. The LMS Algorithm

Each iteration of the LMS Algorithm requires three different steps in the given order. First, the output of the FIR filter $y(n)$ is calculated, according to Eq. (1):

$$y(n) = \vec{w}^T(n)\vec{x}(n) = \sum_{i=0}^{N} w_i(n)x(n-i). \tag{1}$$

Let us add that the symbol $(.)^T$ represents the transposition of the vector. FIR filters are defined by the property of individual coefficients w_i of the vector filter coefficient vector $\vec{w}$. Vector $\vec{w}$ together with the filter order $N = M - 1$ determine the performance of the designed FIR filter (for $M \ni \mathbb{Z}^+ \in N$).

Subsequently, the value of the estimated error signal $e(n)$ is given by Eq. (2):

$$e(n) = d(n) - y(n). \tag{2}$$

And finally, the values of the filter coefficient vector $\vec{w}(n)$ of the particular FIR filter are updated with respect to the next iteration according to Eq. (3).

$$\begin{aligned} \vec{w}(n+1) &= \vec{w}(n) + 2\mu e(n)\vec{x}(n), \\ \vec{w}(n+1) &= \vec{w}(n) + k_\mu e(n)\vec{x}(n), \\ \vec{w}(n+1) - \vec{w}(n) &= 2\mu[d(n) - y(n)]\vec{x}(n), \\ &= \delta\vec{h}(n) \;\; \forall n \in Z^+, \\ \vec{h}(n+1) &= \vec{h}(n) + \delta\vec{h}(n) \;\; \forall n \in Z^+. \end{aligned} \tag{3}$$

The implementation of the LMS Algorithm in $\mathbb{R}$ can be summarized as follows:

Algorithm 1

1: **BEGIN**
2: $\quad \vec{w}(n=0) = \vec{0}$
3: **FOR** $(n = 1, 2, ..., N)$
4: $\quad y(n) = \vec{w}^T(n)\vec{x}(n)$
5: $\quad e(n) = d(n) - y(n)$
6: $\quad \vec{w}(n+1) = \vec{w}(n) + k_\mu e(n)\vec{x}(n)$

The step size (μ) plays a significant role in controlling the performance of the LMS algorithm. This parameter has a major impact on the speed and stability of convergence of the adaptive algorithm. Reaching the optimal value of μ (typically a small positive constant) is necessary for correct function of the LMS Algorithm, whereby:

- If the selected value μ is too small, the time required to find the optimal solution is too long.
- If the selected value μ is too large, the adaptive filter is unstable and it will cause the deviation of the output.

3.2. The RLS Algorithm

Implementation of the RLS Algorithm in $\mathbb{R}$ can be summarized as follows:

Algorithm 2

1: **BEGIN**
2: $\quad \vec{w}(n=0) = \vec{0}$
3: $\quad \mathbf{P}(n=0) = \delta^{-1} \cdot \mathbf{I} \quad \delta \in \mathbb{R}$
4: **FOR** $(n = 1, 2, ..., N)$
5: $\quad \vec{k}(n) = \dfrac{\lambda^{-1}\boldsymbol{P}(n-1)\vec{x}(n)}{1 + \lambda^{-1}\vec{x}^T(n)\mathbf{P}(n-1)\vec{x}(n)}$
6: $\quad \xi(n) = d(n) - \vec{w}^T(n-1)\vec{x}(n)$
7: $\quad \vec{w}(n) = \vec{w}(n-1) + \xi(n)\vec{k}(n)$
8: $\quad t = ACK^R_{time} - \text{mean}(RA)$
9: $\quad \mathbf{P}(n) = \lambda^{-1}\mathbf{P}(n-1) - \lambda^{-1}\vec{k}(n)\vec{x}^T(n)\mathbf{P}(n-1)$

$\mathbf{P}(n)$ is the inverse correlation matrix of the input signal, $\vec{k}(n)$ is the gain vector, $\mathbf{\Lambda}(n)$ is a diagonal matrix consisting of the weighting factors λ^{n-1} (i.e. 1, λ, $\lambda^2 \ldots$). So-called 'adaptation' or 'forgetting' factor λ is in the range $0 > \lambda > 1$ [23]. The parameter influences the process of 'forgetting', i.e. gives more weight to the recent samples of the error estimates compared with the old ones. If $\lambda = 1$, then the estimation is without forgetting, i.e. equal to ordinary method of least squares discussed in the previous section [24]. The weighting factor λ^{n-i} influences the weights, where the input values are considered zero for $i < 1$, and the last n samples are the most significant ones.

For the implementation, the value of forgetting factor is usually set in the range of $0.98 > \lambda > 1$. Small value of λ causes that the filter puts more emphasis on the recent samples of the observed data and tends to forget the past [24]. For $i = n$, i.e. $\lambda^{n-n} = \lambda^0 = 1$, the mathematical expression of the RLS algorithm is reduced on the expression of the LMS algorithm.

3.3. The Evaluation of fECG Signal Filtering Quality

The evaluation of the recovered fECG signals can be both subjective and objective. The subjective evaluation involves the visual assessment of the signal quality by an expert, whereas the objective evaluation uses signal parameters whose values quantify the performance of the applied signal processing method.

Since subjective assessment is quite time consuming and is dependent on the researcher's previous experience, we focused on the use of objective measures to evaluate the performance of our signal processing algorithms. The Signal-to-Noise Ratio (SNR) is one of the most commonly used parameters for the quantitative assessment of filtering performance. It is the ratio of the power in the useful signal compared to that in the noise. The overall signal filtering SNR is calculated by subtracting the input SNR (SNR_{in}) from the output SNR (SNR_{out}). For our purposes (fECG signal extraction) here, the input and output SNRs are defined as follows:

$$SNR_{in} = 10\log_{10}\frac{\sum_{i=1}^{N-1}\left[x_{org}(i)\right]^2}{\sum_{i=1}^{N-1}\left[x_{noise}(i) - x_{org}(i)\right]^2}, \qquad (4)$$

where x_{org} denotes the original (ideal) signal and x_{noise} the undesired signal (mECG).

$$SNR_{out} = 10\log_{10}\frac{\sum_{i=1}^{N-1}\left[x_{org}(i)\right]^2}{\sum_{i=1}^{N-1}\left[x_{rec}(i) - x_{org}(i)\right]^2}, \qquad (5)$$

where x_{org} stands for the original signal (ideal fECG) and x_{rec} symbolizes the signal recovered by the algorithm.

3.4. Dataset

Our main purpose here is not to develop a new model but to focus on a modified version of the already existing models to enable us to address the design, optimization, and testing of our applied adaptive filtering methods for extracting fECG signals. Figure 2 shows a model representing the volume conductor, the position of the maternal and fetal hearts, and the electrode placements. This model is based on the generator designed by Sameni and Behar (see [14] and [15]). Our main purpose here is not to develop a new model but to focus on a modified version of the already existing models to enable us to address the design, optimization, and testing of our applied adaptive filtering methods for extracting fECG signals. Figure 2 shows the exact location of both the maternal and fetal hearts as well as the corresponding electrodes in cylindrical coordinates. The model includes 168 electrodes which are distributed around the maternal volume conductor in two transversal planes which represent the thoracic (TH001-TH096) and abdominal (AE97- AE168) areas.

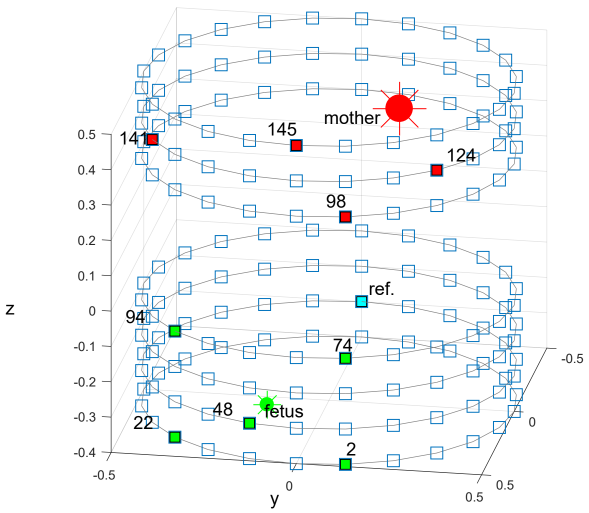

Fig. 2: A model of the human body with electrode placement.

To cover all possible directions around both the maternal and fetal hearts, we chose specific electrode positions for our experiments. The selected abdominal and thoracic positions are highlighted in green and red (Fig. 2), respectively. These electrode selections allow us to optimize our filter settings (as they are position dependent) and enable us to capture all of the possible maternal and fetal VectorGardioGrams (VCGs). Additionally, our experimental electrode placement was chosen to be similar to those used in commercially available devices that perform fHR monitoring [28]. The electrodes used in our experiments are color-coded and their colors represent their functionality (blue for reference electrode, red for electrodes recording the mECG signal from the thoracic area, green for electrodes recording from the abdominal areas - both mECG and fECG signals).

Figure 3 shows an example of the abdominal ECG signal recorded by electrode AE048. The fetal and maternal components are marked in the figure. For signal clarity, only 5 seconds of the signal are shown. It is clear that the fECG signal is hardly noticeable in the abdominal recordings and as such, its extraction would not be possible without effective filtering.

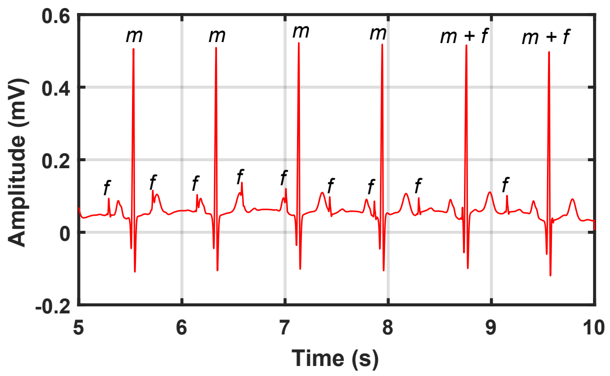

Fig. 3: Abdominal ECG signal containing maternal and fetal components recorded by electrode AE048.

The influence of the Gestation Age (GA) on fetal growth was modeled mainly by increasing the fECG signal amplitude and its frequency, which affected the output SNR value. The higher the SNR value, the better the quality of the fECG signal. In other words, by increasing the GA, the SNR improves. This is in agreement with the theoretical assumption that as the fetal heart grows, the fECG signal amplitude increases. Figure 4 shows this trend for all of the electrode placements used. These information is also summarized in the Tab. 1.

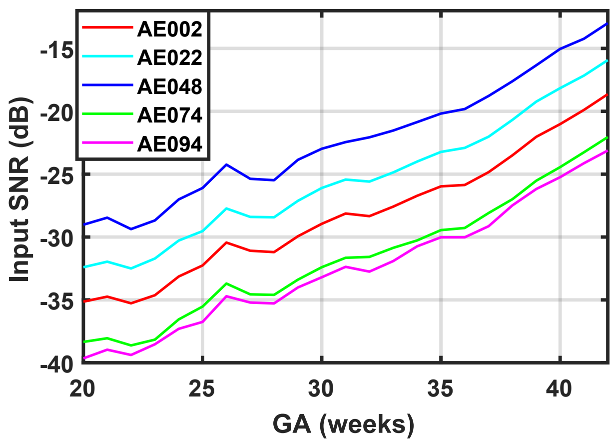

Fig. 4: SNR_{in} values for different abdominal electrodes and GA.

4. Results

We tested the data simulating the GA in the interval from 20 to 40 weeks. These signals were objectively evaluated (by the value of SNR) before and also after applying the adaptive systems based on LMS and RLS algorithms. For each adaptive system, the optimal settings of the algorithms were determined-optimal filter length N_{opt} for both systems, step size μ_{opt} for LMS-based system, and forgetting factor λ_{opt} for RLS-based system. These results are also summarized in the Tab. 1.

From this Tab. 1, we observe that both of the tested adaptive algorithms (LMS and RLS) were able to suppress the maternal component (achieve acceptable results at a lower input SNR value) when the filter setting was optimized. However, we note that the performance of these filters is insufficient until a GA of 30th weeks is reached. Figure 5 shows that the LMS Algorithm outperforms the RLS Algorithm. Based upon this finding, we prefer using this algorithm for fECG signal extraction during the early stages of pregnancy. In contrast, the RLS Algorithm shows better results for higher values of input SNR, for example when a GA $>$ 40 weeks is reached. As such, this algorithm offers a more suitable choice for mHR monitoring during labor.

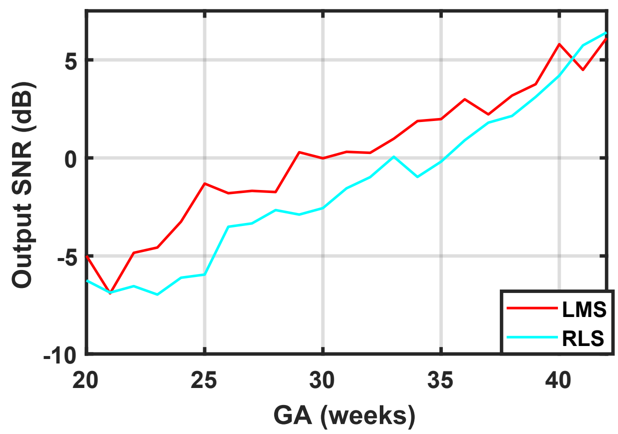

Fig. 5: The performance of the RLS and LMS Algorithms as a function of GA (weeks).

5. Discussion

Figure 6 and Fig. 7 show examples of the ideal (reference) and filtered fECG signals (for a GA of 40 weeks) when using adaptive filters implementing the LMS and RLS Algorithms, respectively. The maternal residue examples are identified by using ellipses (A and B) in both figures. Some residues are small (ellipses denoted as A in Fig. 6 and Fig. 7) - their amplitudes are low and thus could only impact further morphological fECG signal analysis (ST analysis). Nevertheless, we observe residues with amplitudes as large as the fetal components (ellipses denoted as B in Fig. 6 and Fig. 7). Such residues could negatively impact the quality of the fHR detection. An overestimation of the fHR leads to false positives in the diagnosis of fetal hypoxia, which in turn compels the clinician to perform an unnecessary caesarian section.

Tab. 1: Input and output SNR values and their relationship with the gestation age.

	Input SNR_s					Outputs					
						LMS			RLS		
GA (week)	AE002 (dB)	AE022 (dB)	AE048 (dB)	AE074 (dB)	AE094 (dB)	N_{opt} (-)	μ_{opt} (-)	SNR_{out} (dB)	N_{opt} (-)	μ_{opt} (-)	SNR_{out} (dB)
20	−35.14	−32.40	−29.02	−38.34	−39.65	25	0.0094	−4.99	17	1	−6.25
21	−34.74	−31.96	−28.46	−38.05	−38.96	20	0.0119	−6.91	17	1	−6.87
22	−35.27	−32.50	−29.37	−38.62	−39.38	23	0.0080	−4.84	7	1	−6.54
23	−34.63	−31.71	−28.68	−38.16	−38.53	93	0.0092	−4.57	7	1	−6.97
24	−33.14	−30.28	−27.01	−36.55	−37.30	25	0.0097	−3.25	8	0.999	−6.11
25	−32.26	−29.53	−26.10	−35.53	−36.75	24	0.0097	−1.31	7	1	−5.95
26	−30.44	−27.73	−24.24	−33.70	−34.71	24	0.0099	−1.80	7	1	−3.51
27	−31.09	−28.40	−25.37	−34.56	−35.21	22	0.0010	−1.68	7	1	−3.34
28	−31.20	−28.43	−25.48	−34.60	−35.28	22	0.0089	−1.74	16	1	−2.66
29	−29.94	−27.12	−23.86	−33.39	−34.01	24	0.0436	0.29	8	1	−2.89
30	−28.95	−26.10	−22.98	−32.40	−33.20	23	0.0100	−0.02	7	1	−2.56
31	−28.13	−25.43	−22.45	−31.65	−32.37	23	0.0112	0.31	17	1	−1.55
32	−28.34	−25.59	−22.07	−31.58	−32.75	22	0.0086	0.26	8	1	−0.98
33	−27.58	−24.86	−21.53	−30.86	−31.91	24	0.0101	0.98	16	1	0.06
34	−26.72	−24.00	−20.86	−30.27	−30.74	22	0.0116	1.88	7	1	−0.97
35	−25.97	−23.23	−20.18	−29.45	−30.02	20	0.0102	1.98	6	1	−0.19
36	−25.86	−22.91	−19.82	−29.28	−30.02	5	0.0380	2.99	7	1	0.90
37	−24.84	−22.02	−18.78	−28.09	−29.14	20	0.0086	2.22	6	1	1.80
38	−23.50	−20.68	−17.61	−26.99	−27.48	17	0.0120	3.18	7	0.999	2.14
39	−22.03	−19.23	−16.34	−25.52	−26.18	18	0.0120	3.76	7	1	3.11
40	−21.02	−18.16	−15.04	−24.44	−25.24	5	0.0316	5.80	7	1	4.20
41	−19.89	−17.16	−14.23	−23.26	−24.13	20	0.0084	4.49	6	1	5.74
42	−18.64	−15.93	−12.99	−22.05	−23.12	18	0.0104	6.11	6	0.999	6.4

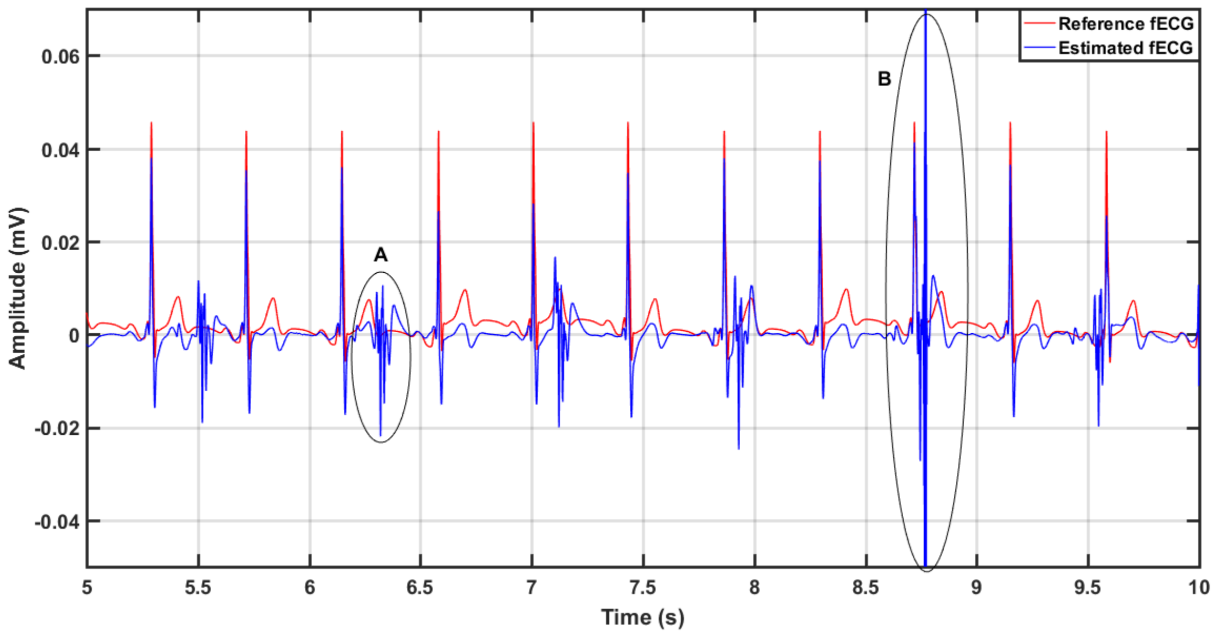

Fig. 6: The output of an adaptive filter using the LMS Algorithm.

Generally speaking, compared to the LMS, the RLS Algorithm is better able to extract fECG signals with a signal morphology comparable to that of the ideal (reference) fECG signal at higher GAs (as shown Fig. 7). However, the LMS Algorithm is more suitable for fHR detection at lower GAs. Additionally, the maternal signal residues produced by the LMS Algorithm are of lower amplitudes. Nevertheless, the ability of this algorithm to suppress the maternal component more than that achieved by the RLS Algorithm suppresses the fECG signal as well (Fig. 6). This could influence the fHR determination and reduce the value of the estimated fHR and thus lead to a possible false negative diagnosis of fetal hypoxia. The results reported here are based on experiments that were performed for the most common fetal position (vertex presentation). In our future research we plan to test the performance of our adaptive filters for a variety of other fetal positions.

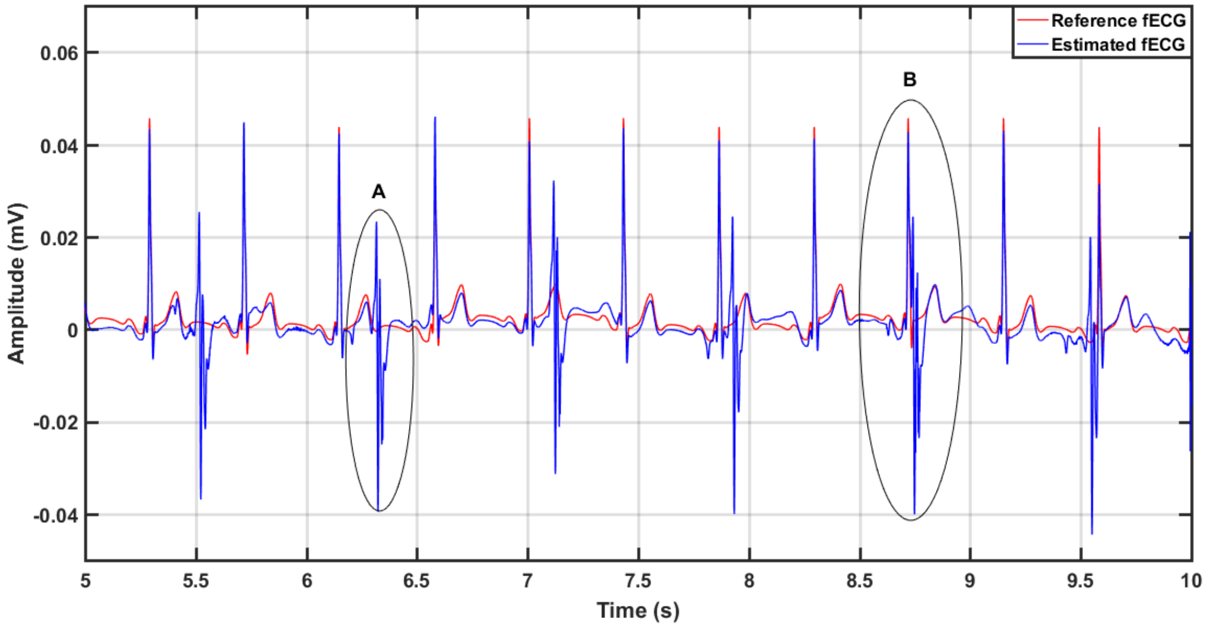

Fig. 7: The output of an adaptive filter using the RLS Algorithm.

6. Conclusion

Our research showed that the performance of adaptive filters (using the LMS and RLS Algorithms) to extract fECG signals from aECG signals vary as a function of the fetal gestation age. We demonstrated that with proper settings, these algorithms were able to extract the fHR information effectively as early as 30th week of GA.

Based on our results, we conclude that the RLS Algorithm is more effective in fECG signal extraction at a high GA (for example during labor). In contrast, the adaptive filter using the LMS Algorithm outperforms the RLS Algorithms in earlier stages of pregnancy and thus is more suitable for such cases. We believe that optimized adaptive systems have the potential to be used not only for fHR detection but also for fECG signal morphological analysis.

In our future research, we intend to test the influence of different fetal positions (besides the most common vertex presentation) on the performance of such adaptive systems. Moreover, we plan to verify our synthetic results by using adequate real data acquired from clinical practice. Since real data are not currently available, we have initiated a collaborative arrangement with our University Hospital to address this limitation.

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