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An Application of Modified Filter Algorithm Fetal Electrocardiogram Signals with Various Subjects

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ABSTRACT

Electrocardiogram (ECG) is bio-medical signal processing main theme research focus. This is due to the cause of the massive advance in digital computer that makes automation in detection of several disease by using bio-signals data. Monitoring the fetus heart during labor and pregnancy of the maternal is highly recommended. This process can reduce the risk of the fetus being born later with bad sickness. There are several factors that trammel the ECG result and one of it is the noise from electromyographic (EMG) from electrical maternal muscle activities. The noise could come from the abdominal movement or contractions that cause massive noise that often failed the machine detection accuracy. In this study, a modified filter algorithm is offered to remove the electrical noise from the recorded fetal ECG signals. The results show that the noise was reduced significantly, and the signal become smoother. The experiment was conducted using 3-lead ECG recorder.

Keywords: Electrocardiogram, Filtering, Extraction, Bio-signal, Annormalities, Accuracy.

Mathematics Subject Classification: 53B50, 90C90

Computing Classification System: I.4

1. INTRODUCTION

An electrocardiogram (ECG) is a bio-signal method used to obtain certain information about the subject heart condition, the data recorded is often later interpreted to determine what medication to be done or as a way of prevention by detecting early symptoms of heart problems. Practitioners and physicians that study on cardiac monitoring heavily relies on ECG. Monitoring of subject heart usually is conducted to get data from the subject heart muscle activities in a longer time span. It can provide enough data to find out the faced problems and help the diagnosis. The abnormalities detected can be a deciding factor for either the subject decision or the doctor specialist. It can have several unique characteristics, but the cause must be known in certain, is it caused by gene factor or is it really caused by a disease that affect heart or other heart problems. The ECG records heart muscle electrical activity and then display the data in a form of a linear graph on a screen or on paper. This data could then be interpreted by a medical practitioner to determine the condition of the subject's heart. Irregular heart rhythm and damage on the heart muscle can affect the ECG result. ECG test is usually recommended for people that show any sign of heart disease judging by family history of heart disease, smoking, overweight, diabetes, high cholesterol or high blood pressure. An ECG test is also recommended when the subjects is experiencing symptoms such as chest pain, asthma, feeling dizzy, easy to faint, and tachycardia (fast heartbeats) or irregular heartbeats (palpitations). ECG test is mostly conducted to monitor people with heart problems, to determine which medications on the heart should be done or the use of artificial cardiac pacemakers.

In order to do an ECG test, there is no restriction on food or drink. The three major types of ECG are(Pan, Tompkins, 1985; Kohler, Hennig, Orglmeister, 2003; Turnip, Rizgyawan, Kusumandari, Hermida, 2016): (i) Resting ECG – In this type of test subject cannot move at all during the test and is recommended lying down to reduce EMG noise that could obstruct the ECG result.The duration of this ECG is usually five to ten minutes. (ii) Ambulatory ECG – Usually it is done by wearing ECG recorder that have less wiring and easy to be taken outside and the duration of data acquisition is around one day. Movement is allowed during this type of ECG; this type of ECG is mainly for people that have certain condition where the abnormalities in ECG data appear and disappear in irregular rhythm. This ECG is also for people that are recovering from heart attack.Any symptoms that appear during the recording must be recorded manually as a reference to the ECG result later. (iii) Cardiac stress test – this ECG is conducted while the subject having exercise like walking on a treadmill, this usually done to athletes especially runner and the duration for the test is usually around fifteen to thirty minutes.

The result of the ECG test will determine what treatment is needed. ECG can diagnose several heart problems including(Scheidt, 1984, Afonso, et al., 1999): arrhythmia, heart defect, Tachycardia, Bradycardia, enlargement of the heart, irregular heartbeats, damages to heart muscles, abnormal heart deviation or position, Pericarditis, Myocarditis, cardiac arrest, and many more. On rare occurrence a normal ECG result could be obtain from subject with heart problems if the symptoms do not cause affect heart muscle electrical activity.

In the last few years, the advanced methods have been applied to analyze the ECG signals such as heart rhythm, heart beat rate, arterial pressure, EMG and respiratory signals (Netter, 1971; Amri, Rizqyawan, Turnip, 2016; Kasar and Joshi, 2012). To identify the time-varying spectral characteristics of the ECG signals process, most of the methods are computed in time variation of the their statistical properties. Various types of algorithms have been widely studied and tested in recent years in improving the ability of ECG sinal classification both offline and in real time. An artificial neural networks has been used to classify whether the patient is suffering from arrhythmia (Vishwa and Sharma, 2011). Comparative study of the ability of classification techniques with supervised and supervised learning methods has been applied to ECG signals. (Silipo, 2011; Pan, Tompkins, 1985; Kohler, Hennig, Orglmeister, 2003; Turnip, Rizgyawan, Kusumandari, Hermida, 2016; Turnip, Rizqywan, Kusumandari, Turnip, and Sihombing, 2017). Other techniques present the development of feature extraction algorithms from a number of available features (Li, Gao, Chen, 2012; Oduguwa, Tiwari, Roy, 2005; Tomescu et al., 2007; Garcia et al., 2011; Shams, Rashedi, Hakimi, 2017). One of the goals and benefits of using the feature extraction process is to minimize processing time and development costs while speeding up the time for classification and testing training. Feature selection also plays an important role in increasing classification accuracy and eliminating irrelevant features.

ECG obtained from maternal abdomen lead combined with maternal chest lead, can be used to monitor fetal heart electrical activity. For safety, monitoring of fetal heart rate and movements during pregnancy in this study used a non-invasive recording device. Existing tools like cardiotocography is still can be used due to the advance of technology, but it does not support monitoring with long duration, also CTG may lead to error in the recognize of fetal heart rate. In analyzing the fetal ECG, a preprocessing phase is needed. The filtering algorithm of the recorded fetal ECG is analyzed.

The main contribution of the signal preprocessing aspect is by using a modified filter algorithm to reduce electrical noises in the real time and wireless recorded data. The focus is thus to extend the existing methods to further improving the result. FIR and Butterworth Algorithm will be integrated and used for this study. The integration is proposed not only to increase the robustness of the method, but also to improve the result data. The method is then tested on the recorded fetal ECG data. The lack of existing reliable database requires us to record our own data set. The data is recorded using 3-lead ECG modules BITalino. However, because there is no existing study that used the same method to record the fetal ECG, electrodes lead placement adjustment for each subject is needed. The method is finally evaluated on experimental data and its efficiency is analyzed on data recorded directly from several subjects of pregnant women, which to further test the proposed method of recording and filtering the data (Noorzadeh, 2015). In the ECG-complex, the P-wave represents the deplarization (pumping) of the upper heart chambers (atria). The QRS-complex represents the depolarization of the lower heart chambers (ventricles). The T-wave represents the repolarization (recovery) of the heart chambers (ventricles). The T-wave in relation to the amplitude of the QRS-complex (T-QRS ratio or T/QRS), and the shape if the ST segment.

2. METHOD AND EXPERIMENT

2.1 Data Acquisition

Before the extraction of ECG there are several processes and steps that need to be prepared. The first thing that must be considered in the ECG recording process is the electrodes placement patternand the recording device specification. This is because different lead patterns will affect the desired waveform. In addition, the specifications of the recording device can also affect the credibility of the recording data that will be used. In recording ECG signal there are several techniques can be used which listed in the following, the first is the Standard Clinical ECG that uses 12 leads. The 12 ECG leads method is divided into 3 groups, Bipolar leads, Unipolar Extremities, and Unipolar Precordial. Lead Bipolar namely lead I, lead II, and lead III. Unipolar Extras leads consist of aVR leads, aVL leads, and aVF leads. Whereas Unipolar Precordial leads are leads V1 to V6 (Jin, Wulff, Widdicombe, Zheng, Jie, Puglisi, 2012). In addition, there is a vector cardiogram technique that uses

3 leads to record an ECG. Body potential is modeled as a vector of 3 dimensions with bipolar leads using 3 leads. This was first introduced by Einthoven in 1903. In the experiment, several lead placement adjustments were done in the abdominal area to determine which are the best ones in order to get a decent result in the recording.

The module that used in this research is BITalino (Guerreiro, Jose, Martins, Silva, 2013). BITalino is designed to be able to record ECG signal with efficiency and effectivity. From many other modules, each one of them has its pros and cons. BITalino is chosen because the fact that it is easy to use, have many functions and low price. It also can be used either for research purpose and even on a daily basis. In the Figure 1, it will next be shown the BITalino module and the lead placement that are used in this research. BITalino use 3-Lead Electrode Cable that consist positive (+), negative (-) and neutral or ground. ECG signal is basically a measurement of the electrical activity from the heart muscles. Intercadiac signals, generated by the action potentials of the different cardiac parts, pass through various body layers, and then the data acquisition process through the electrodes. The signal should be able to experience various effects and penetrate through a complex system.

For pregnant subjects, usually are measured by collecting the data from two locations in the body, one is from the chest and then the abdomen. The fetal ECG is commonly extracted from multiple several lead of electrodes. One of the many methods is by measuring electrical activity from three electrodes on chests (maternal) and five electrodes on abdominal (composite), however, the data accumulated can vary depends on the techniques used. The chest electrodes collect the maternal ECG with a vain of impact from the fetus ECG. On the other hand, the abdominal electrodes detect the composite signal that consists of both contribution from maternal ECG and the fetal ECG. The Result of ECG-test depends on the position where the signal is recorded. Many can affect the intracardiac signal distinctively mainly from leads position to variation of heart deviation. The model of the heart electrical activity is formed as being induced by a current dipole that are time dependent, variable in the two amplitude an orientation. As the result, the interpretation of additivity and the correlation between the signals acquired from maternal abdomen and maternal chest become questionable. Despite the locations of the waveforms constructing a full cycle of the PQRST, the ECG remain relatively unchanged for various lead positions, the resemblance drastically varies between various signal profiles. Therefore, to extract the fetal ECG from the composite signal with complete robust, it is needed to apply those features of the signal that remain relatively invariant with respect to the lead position. Since in this study the module used was a 3-lead electrode support only several pinpointing and adjustment is done in the abdominal area until the result show a satisfying record (Khamene and Negahdaripour, 2000).

The next stage is preprocessing ECG recording data to be used for extraction. In the ECG recording stage on the subject, various factors can appear that can affect the results of the recording data. As a result, undesired data is included in the recording and makes data accuracy low. In addition, the level of difficulty will increase when extracting the feature of the ECG wave. The main core of the preprocessing stage is the filtering process, where parts of unused data that will be deleted. Finite Impulse Response (FIR) and Butterworth Filter algorithms are used in the filter process. The parameter design of the FIR filter uses a cutoff frequency of 0.5 - 40 Hz. The basic characteristics of the FIR filter are shown in (1).

$$y(k) = \sum h(k)\,x(n-k) \tag{1}$$

In equation 1, $x(n)$ is the input, $y(k)$ is the output and $h(k)$ is the FIR Filter's response frequency coefficient. The Butterworth Filter algorithm itself consists of 2 types, namely: Lowpass Filter with a 25 Hz cutoff frequency and Highpass Filter with a 3 Hz cutoff frequency. In Butterworth's research shows that Lowpass Filter is designed as in (2), which can be modified into Highpass Filter and Notch Filter (Butterworth, 1930).

$$G(\omega) = 1/\sqrt{(1+\varepsilon^2(\omega/\omega_c)^{2n})} \tag{2}$$

where $G(\omega)$ shows the response frequency, ω is the angular frequency in radians per second, n is the number of reactive elements in the filter, ε is the maximum value of passband frequency, and ω_c is the cutoff frequency. FIR filters have the impulse response of finite duration and can be implemented without feedback. FIR use several window techniques which listed below (Chandrakar, Yadav and Chandra, 2013):

- *Rectangular window*: - the weighting function of rectangular window is given by

$$\omega_{\mathrm{R}}(N) = \begin{cases} 1,\ for\ |N| \le \dfrac{M-1}{2} \\ 0, otherwise \end{cases} \tag{3}$$

- *Kaiser window*: - Kaiser window is designed with a maximum stop band width and minimum stop band attenuation for FIR filter with side love attenuation of β dB, α parameter affects the side lobe attenuation of the Fourier transform of the window is given by

$$\alpha = \begin{cases} 0;\ \beta \le 21 \\ 0.5842(\beta-21)^{0.4} + 0.07886(\beta-21);\ 21 < \beta \le 50 \\ 0.1102(\beta-8.7);\ \ \beta > 50 \end{cases} \tag{4}$$

where $\beta = -20\log_{10}\delta_3$;

- *Hamming window*: - The Hamming window function can be expressed as

$$\omega(n) = \begin{cases} 0.54 - 0.46\cos\dfrac{2\pi n}{N-1}, 0 \le n < N-1 \\ 0 \qquad\qquad\qquad\qquad , otherwise \end{cases} \tag{5}$$

- *Blackman window*: - The Blackman window function is given by

$$\omega_s(n) = \begin{cases} 0.42 - 0.5\cos\dfrac{2\pi n}{N-1} + 0.08\cos\dfrac{4\pi n}{N-1}, 0 \le n < N-1 \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad , otherwise \end{cases} \tag{6}$$

The fetal ECG could have many noise due to several factors, including: the Maternal ECG is mixed with the fetal ECG during the recording through abdominal surface electrodes; interference from maternal EMG that cause high amplitude noise; the fetal heart is still small and in the process of developing, therefore ECG result with weak and low amplitude is to be expected; Variation of fetus position inside the womb; proper placement and right adjustment are the critical point. Noninvasive fetal ECG clearly have its own limitation compared with the old version invasive one that can directly extract data from the fetal scalp. Many of the research have applied and suggested varies different approach. However, up to now, there is not a unique reliable solution to the problem. A schema of the adaptive filtering for fetal ECG can be shown in Figure 1.

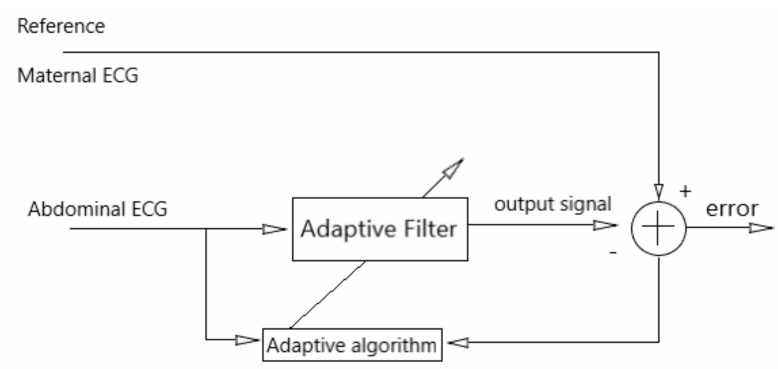

Figure 1. Schema of the adaptive filtering for recorded fetal ECG.

The biomedical signal in this study is in the form of an ECG signal that is processed by involving a combination of FIR filter and IIR filter (Butterworth filter) with frequency of the ECG signal about 0.5 Hz – 100 Hz. This ECG signals normally contaminated by various noise or artifacts (Kumar, Ahmad, and Rai, 2012)such as power line interference, motion artifacts, muscle contraction, base line drift, and the noise from electronic devices.

2.2 Experiment

The main purpose of this study is to enable the application of heart monitoring to be easier without interfering by daily labours. Using practical tools such as BITalino all the needed information for supervision could be well obtained. The experiments were designed for the subjects so they can monitor their heart condition along with some basic activities. There are 15 volunteers with 6 to 8 months of pregnancy involved in the experiment. Each subject is recorded within 2 minutes by 1000Hz sampling speed. A CTG test is first performed to determine the fetal heart rate so we can match the result data later. Each subject first conducted an interview, examined the doctor with USG, filled out informed consent, and filled in the questionnaire. The results of both the doctor's examination and the doctor's next will be used as a reference to the measurement results and processing of ECG signal records. During the experiment, each subject was accompanied by a midwife and experimenter. When the experimenter installs the sensor, the midwife plays a role in determining the position of the baby in the womb. The baby's position is crucial to the quality of the recorded signal, which is the result of recording the baby's heart rate. At the time of recording, in addition to the baby's heart rate, the mother's heart rate was recorded as well as subsequently considered noise. The sensor is mounted in three positions based on the position of the baby in the womb. The scenario of the experiment is shown in Figure 2.

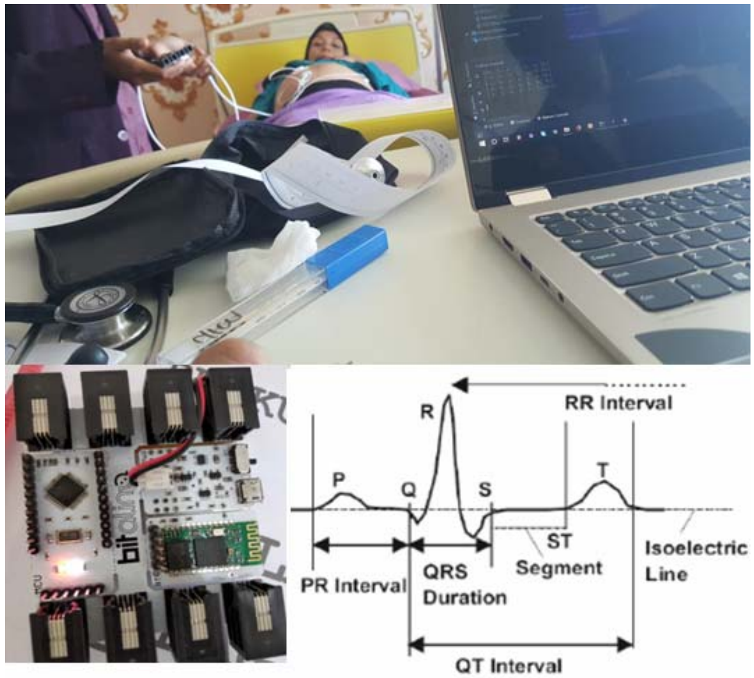

Figure 2. Experiment sheme and BITalino sensor system.

3. RESULTS AND DISCUSSIONS

Skin stretch that causes alter the impedance of skin around electrode is what mostly caused electrode motion artifacts. Motion artifacts are more problematic to handle rather than baseline wander because their spectral content overlaps the PQRST complex. It usually occurs around 1 to 10 Hz. The EMG noise also contribute as a major problem in the ECG result, since low amplitude waveforms can be obscured completely. EMG is not removed by narrowband filtering. Since the ECG is a repetitive signal, techniques can be used to reduce muscle noise in a way like the processing of evoked potentials (Figure 3).The electromagnetic field and the electrical cable lines are one of the most common disturbances that interfere with ECG signal. Other bioelectric signals in the abdomen subject recorded on the surface of the abdomen are also potential sources of interference. The disturbance usually appears at a frequency of about 50 or 60 Hz in sinusoidal form, can also be accompanied by some harmonics. A damaged electrodes cable could also cause this problem and cause a straight signal like Figure 4.

Another problem that might occur is powerline interference. Cables that carry ECG signals from the subject to data recording equipment are susceptible to power frequency electromagnetic interference which generally affects signal quality. Signals with these disturbances are often a challenging problem considering the frequency of the source of the interference varies and depends on time changes. Indeed there are still some other technical difficulties, but what often becomes an obstacle is when the interference involved in the data has a low frequency (Ziarani and Konrad, 2002). While the powerline interference frequency shown significant reduction as in Figure 5 there is still no solution if the powerline cutoff or damaged that cause the ECG signal to be lost.

The result shows significant noise and artifacts reduction from the proposed method in Figure 6. However, based on the subject month of pregnancy and due to the weak and low amplitude it is hard to detect the actual graph of fetal heartbeat. Based on the subject month of pregnancy and due to the weak and low amplitude it is hard to detect the actual graph of fetal heartbeat. Even so, the result shows significant noise and artifacts reduction from the proposed method. Based on the performance the method of filtering algorithm has a satisfactory performance and is suitable to be applied, while the fetal heartbeat method itself still needs improvement. A continuation of this study is possible but first the problem of weak and low amplitude of fetal ECG needs to be solved. A way to amplify this weak ECG is needed and will be studied more in the future.

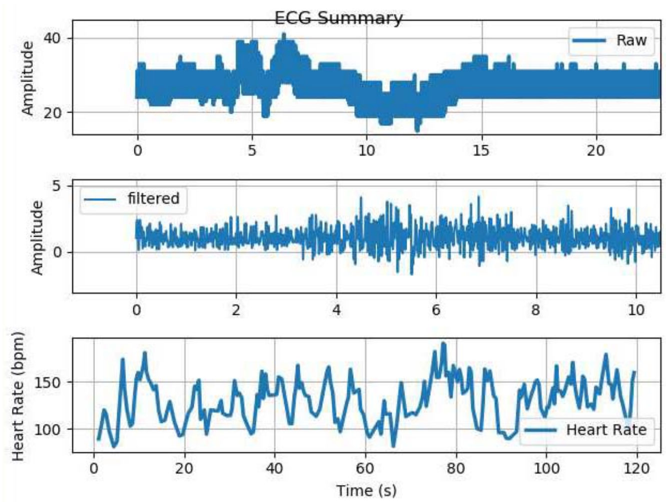

Figure 3. Fetal ECG affected by electrode motion artifact.

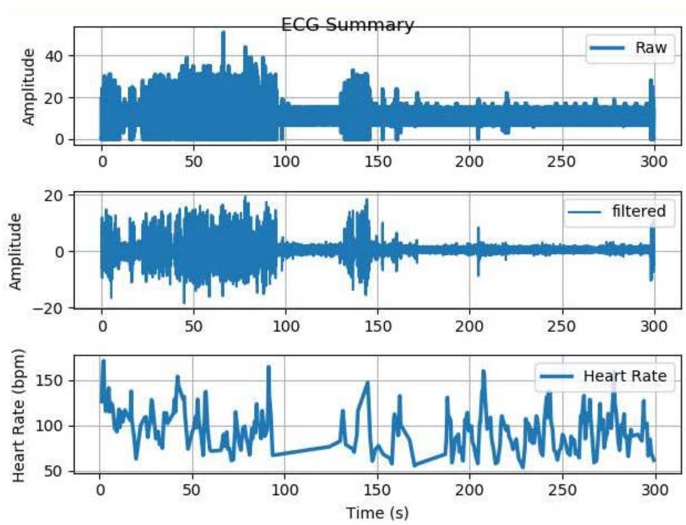

Figure 4. Fetal ECG signal with electromyographic (EMG) noise.

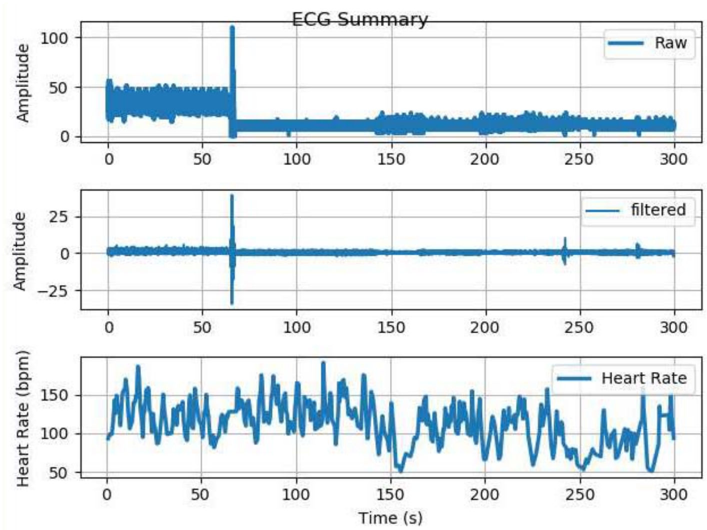

Figure 5. ECG affected by powerline interference.

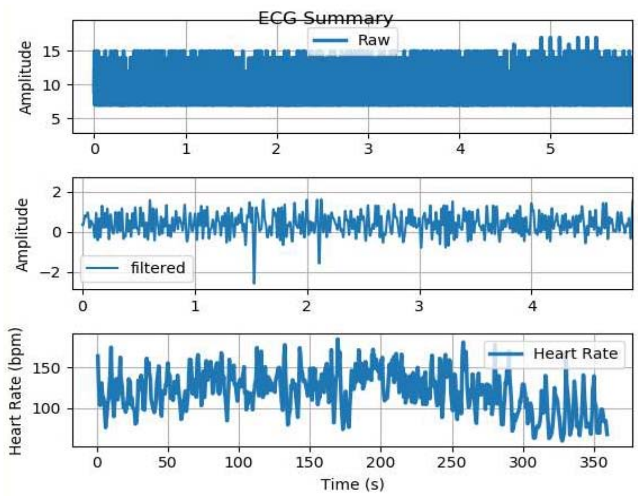

Figure 6. Removal of all noise and artifacts from the recorded fetal ECG.

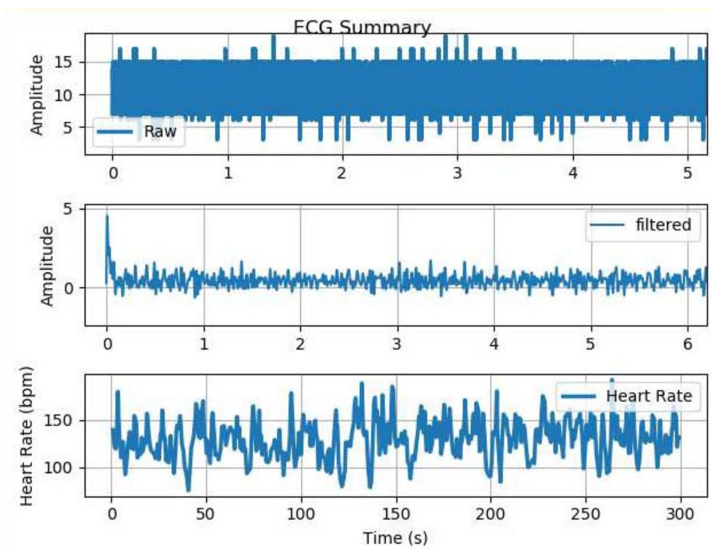

Figure 7.Weak and low amplitude fetal ECG.

4. CONCLUSIONS

Complete information about all ECG features is crucial in supervising and monitoring subject's heart condition. Before the extraction of fetal ECG feature, noise and artifact need to be filtered. The modified filtering algorithm using the integration of the FIR and Butterworth algorithm was used to reduce the recorded fetal ECG noise and artifact.

The results show a good performance of the proposed algorithm. The results of the fetal heartrate method itself still need improvement by amplifying the fetal ECG. In addition, it was found that the recorded data with high noise and artifact provide a higher level of difficulty in filtering the fetal ECG. The heart defect needs to be diagnosed early, for the proper medication can be selected to cure the subject that have certain illness that involves heart.

Further developments in fetal ECG knowledge and technology field is crucially needed for an effort to reduce fetal heart problems that happens during pregnancy and to gather accurate information so further medication can be developed or employed.

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