Original Article

Wearable Fetal ECG Monitoring System From Abdominal Electrocardiography Recording

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Abstract

To find dangerous situations for the foetus, foetal monitoring during pregnancy is crucial. Cardiotocography is the industry-standard procedure for evaluating the health of a foetus inside the womb (CTG). Unfortunately, CT can only be used in a clinical setting since it calls for experienced doctors and heavy equipment to be used. A novel prototype for foetal monitoring is presented to address the drawbacks of CG, which impede a close and continuous monitoring during the latter weeks of pregnancy. We show a foetal monitor that can be worn at home. It is based on the recording of abdominal ECGs as opposed to Doppler Ultrasounds, which CT uses to find foetal heartbeats. Eight leads implanted in a wearable belt are used by the system to measure the maternal and foetal ECG. An original algorithm was created for recognition. he data collecting circuits, data transmission module, and signal analysis platform that underpin the ECG monitoring system have low input-referred noise, high input impedance, and high resolution. The FECG is separated from the AECG signals using the adaptive dual threshold (ADT) and independent component analysis (ICA) algorithms. Pregnant women in three different positions have their AECGs recorded and evaluated to verify the effectiveness of the proposed approach (supine, seated, and standing). The outcome demonstrates that the suggested technology can record the AECG in various postures with good signal quality and high accuracy in foetal ECG and heart rate data. The performance of the foetal QRS (fQRS) complexes extraction is assessed using the metrics of sensitivity (Se), positive predictive accuracy (PPV), accuracy (ACC), and their harmonic mean (F1). For the fQRS complexes extraction, the average Se, PPV, ACC, and F1 score are 99.62%, 97.90%, 97.40%, and 98.66%, respectively. This study demonstrates a promising use for the suggested technology in foetal health monitoring.

Keywords: fetal; electrocardiography (ECG); health status; monitoring system; fetal heart rate (FHR)

INTRODUCTION

Doppler ultrasonography, invasive fetal electrocardiogram (FECG) monitoring, and non-invasive FECG monitoring are currently the most popular methods for fetal health monitoring. Doppler ultrasound is a common monitoring technique used throughout pregnancy and delivery [1]. Heart abnormality is a significant factor in perinatal stillbirth globally, whereas perinatal complications account for over 40% of all perinatal and maternal deaths [2]. Therefore, during pregnancy or birth, it is crucial to keep an eye on the fetal heart rate (FHR) [3]. IoT or the "internet of things," is a phenomena that involves connecting people, machines, and other objects to the internet in order to share data continuously and identify one another based on certain characteristics [4], using sensors for real-time tracking, monitoring, and data management. Governments in many nations are allocating substantial sums of money to fund research projects aimed at eradicating medical negligence, one of the major flaws in the healthcare system. This means that the transformation that the world needs to see in the healthcare sector will be big and long overdue. In nations like India, where the population is expanding quickly, access to appropriate healthcare and monitoring becomes a serious issue because there aren't enough doctors to treat everyone in the country. As a result, some really skilled and effective doctors must travel across the nation to examine patients. On this situation, the doctor must carefully monitor his patients' conditions and store their data in the cloud in order to understand their current state and make the appropriate next measures. Continuous monitoring of the patient and storing the monitored data to the cloud find importance, for instance, if a doctor performs an operation in New Delhi and must depart for Kolkata the same day in order to inform the doctor of the details of the patient he had operated on in New Delhi. Using the internet, the doctor may quickly review the monitored data and provide advice as necessary [5]. Cardiotocography (CTG), the current gold standard for FHR monitoring, shows both FHR and uterine contractions visually. However, CTG only offers an estimate of the FHR, is susceptible to signal loss, and cannot be used for extended periods of time. During pregnancy and delivery, Doppler ultrasound is frequently used [6]. Using signal processing techniques, procedures using the abdominal electrocardiogram (AECG) have a better chance of long-term monitoring of FHR and fetal health. By placing a pair of electrodes on a pregnant woman's belly, it is possible to collect the fetal ECG, an electrical signal, without using any kind of invasive procedure [7,8]. According to studies, a fetal electrocardiogram (FECG) gauges the fetal heartbeat and may give rhythm and morphological details such the PR and QT intervals or ST segments [9]. A practical method for the early detection and diagnosis of fetal congenital cardiac disease and distress is FECG monitoring [10]. A continuous monitoring of physiological signals is now possible thanks to recent advancements in information and communication technologies (ICT). Previously, some connections and transmission rate restrictions only allowed for the real-time collection and transmission of a small number of parameters. Studies show that patients are willing to adopt remote management of chronic diseases as a result of the development of new tiny sensors and equipment, along with advancements in wireless transmission [11]. Nowadays, many healthcare sectors view the transition to domiciliary care for non-critical medical concerns as a way to improve control over chronic diseases and, as a result, delay the emergence of any complications, minimise unnecessary hospitalizations, and lessen burden on national finances [12]. Fetal scalp electrocardiography (SECG) and maternal abdomen electrocardiography are two practical methods for gathering FECG signals (AECG). Accurate foetal heart rate and FECG morphology can be obtained with SECG (FHR). Nevertheless, SECG is intrusive, costly, and labor-intensive. Contrarily, AECG is affordable, practical, and safe for both the mother and the foetus throughout the pregnancy. Additionally, AECG can be used in earlier weeks (>20 weeks), but SECG only keeps track of the fetus's wellbeing during delivery. Therefore, the creation of a non-invasive FECG (NI-FECG) monitoring system is crucial for the early detection of heart illness, which can enhance the efficacy of the fetus's proper therapy. Non-invasive physiological measurement is currently a growing new trend [13]. Putting in place a home-based NI-FECG monitoring system presents two key technological hurdles. The wearable FECG monitoring system's practical hardware acquisition module, which makes sure the maternal AECG signal is continually recorded in various conditions, presents the first difficulty. Second, to effectively apply professional expertise to the pregnant woman's AECG signal, accurate and real-time waveform analysis is necessary.

Traditional ECG detection is combined with electronics, information, artificial intelligence, and other cutting-edge technology to provide wearable ECG monitoring, which is becoming more and more common in the movement toward autonomous health monitoring [14,15,16,17,18]. In instance, the amplitude of the maternal ECG (MECG) is frequently several times that of the FECG in the ECG signal obtained from the abdomen, making the extraction of the FECG rather challenging [19].

With the development of electronic and communication technology, smartphones have been popularized and are now in millions of households. To realize home-based fetal ECG monitoring, this paper proposes a fetal ECG monitoring system based on smartphone technology. Three-lead abdominal ECG signals are collected by a wearable fetal ECG collector, and then the collected abdominal signals are sent to a smartphone app via Bluetooth. The smartphone app pre-processes the three-channel abdominal ECG signal and uses the fast independent component analysis (ICA) algorithm to separate the source components. Then, the smartphone app uses the sample entropy to detect the fetal ECG signal and calculates the fetal heart rate. Finally, the fetal ECG waveform and fetal heart rate are displayed in real time on the smartphone interface, and a warning is given when the heart rate is abnormal.

Contactless ECG sensors provide the convenience of monitoring in nonhospital environments [43]

Diverse ECG measurement systems have been reported including systems that can be fixed to chair [44], bed [45] or can be adapted to clothes [46-48], Nemati et al.[49] demonstrated a wireless ECG monitoring system which consisted of a belt stretched inside a T-shirt and equipped with three capacitive electrodes ,where the ECG measuring is transmitted to a PC, requiring the user to own a PC. However, once this proposed system is preferred, the patients can use their existing cell phone for monitoring the vital signs. Mahmud et al [50] collected ECG signals using two electric potential integrated circuit sensors fitted in a phone case and were able to transmit the signal with an Rfduino through Bluetooth low energy (BLE) and displayed the ECG signal on a cell phone. They also use smart phone memory to save ECG data, which is not appropriate for multiple usages due to limited data storage. In this paper,both local memory and server are implemented to allow multiple patient follow-ups without limitation to data storage. Chamadiya
et al.[51] performed ECG measurements with electrodes fitted on stretchers, wheelchairs, and patient beds. They installed the conventional Ag/AgCl and TE on the same measurement setup to compare the results of both electrode types and concluded that there was no discrepancy between the measurements of the two types. In their work, the patient had to be stable in the supine position dictated by the measurement system or had to maintain contact with electrodes reclining back in a chair, which restricts the movement of the patient. On the other hand, in this paper, the person does not need to recline against or maintain contact with anything and hence, favorable since the ECG is acquired under normal motion and living conditions. Pani
et al.[51] concluded that ECG devices as wearable devices, using either dry or wet TE, without any discomfort to the patients. TE is used in this paper as well. For remote monitoring, a smartphone, an Internet of Things (IoT) server, and a web interface are implemented in the system. To monitor ECG, Yoo et al.[53] developed a 24-h data acquisition system comprising TE in a smart dress. However, they reported ECG signal without heart rate (HR) or location. Lam-onaca et al.[54] equipped a smartphone with new sensors and used existing sensors on the smartphone to measure the body posture, falling, HR, blood oxygen saturation, eye pathologies ,and respiratory system. Their system does not have a wearable part, and the HR was calculated using captured face image providing an added benefit for the user in case of instant HRmeasurement [55].

The aforementioned methods seek to divide the underlying statistically independent sources into three parts: noise, FECG, and MECG. A linear stationary mixing matrix between the resources is the main presumption of the techniques. The quality of the FECG extraction increases with the quantity of abdominal recordings available. However, a pregnant lady would need to have multiple electrodes placed on her in order to generate such a high number of recordings, which could be painful for them and make it challenging to use the process while going about daily activities. The complicated electrode configuration has a negative impact on the above techniques' clinical utility. The second category of approaches consists of temporal techniques that estimate MECG and deduct it from AECG [20] . The analysis of the FECG signal is still in its infancy, despite the fact that there has been a tremendous advancement in ECG signal processing in recent years. On the basis of AECG recordings, several pieces of literature on the location of the foetal QRS (fQRS) complexes have been provided [21] . Convolutional neural network is one of the techniques suggested in the literature (CNN)[22]

,template selection [23], the least mean square (LMS) adaptive filter (AF), the recursive least square (RLS) adaptive filter[24], Kalman filtering (KF)[25], independent component analysis (ICA)[26], periodic component analysis (πCA)[27], principal component analysis (PCA), wavelet transform (WT), the echo state neural network (ESN), and fusion of different methods (FUSE method) etc [28]

The goal of this work is to design a portable, home-based FECG monitoring device that can be utilised for ongoing foetal health monitoring. The following are the contributions made by this work;

1. A high-precision, low-noise portable ECG measure device is built and tuned to gather pregnant women's abdomen ECG signals in various situations since foetal ECG is very weak and susceptible to noise (supine, seated, and standing posture). The system consists of biocompatible electrode materials, a noise suppression design and amplification circuit, data transmission, and storage module.
2. Accurate FECG signal extraction in the presence of background noise and maternal artifacts is a key requirement in non-invasive AECG recordings analysis.

Following is an outline for this essay. Short descriptions of the FECG monitoring system's design are provided in Section 2. Algorithm for signal analysis is shown in Section 3. The experiment designs and findings are covered in Section 4. The topic is provided in Section 5. The final step is drawing the conclusion.

MATERIALS AND METHODS

Figure 1 depicts the foetal ECG monitoring device. A three-lead foetal ECG collector was our creation. Pregnant women's three-channel abdomen ECG data were gathered using five electrodes. The five electrodes were applied to pregnant women's bellies using a straightforward, simple-to-learn pasting technique. Through Bluetooth, the three-lead abdominal ECG signals were gathered and sent to the smartphone. In order to collect foetal ECG data in real time, app software based on smartphones was created. The smartphone screen showed the foetal ECG that had been retrieved. For an abnormal foetal heart rate, a warning was issued [29].

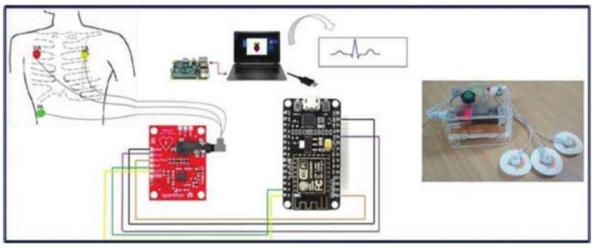

Figure 1: Proposed Hardware Prototype For ECG Monitoring System

Design of FECG Monitoring System

Figure 1 shows the frame diagram for the foetal monitoring system. The data gathering module, data transmission module, signal storage module, and signal analysis platform make up the majority of the monitoring system. For the purpose of gathering the AECG signals from pregnant women, electrodes will be applied to the skin in a certain manner. The AECG signals, comprising maternal and foetal ECG signals, are filtered, amplified, and converted from an analogue signal to a digital signal by the signal acquisition module. The abdominal ECG signals are either stored on a memory card or transmitted over Bluetooth via the signal transmission module to the PC interface. The AECG waveform is displayed by the signal analysis platform, which also processes and analyses the AECG data.

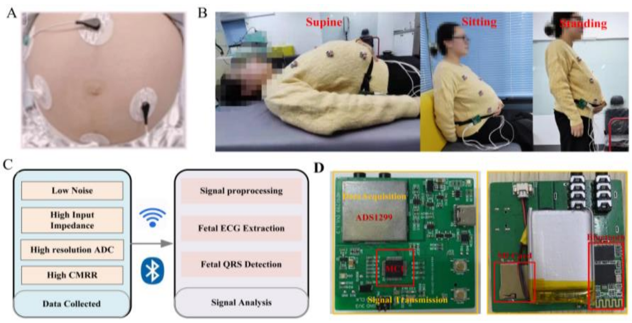

Figure 1. The Diagram Of The Fetal Monitoring System Frame. (A) Electrode Placement. (B) Postures Of The Subject. (C) Monitoring System. (D) Hardware Prototype.

ELECTRODES;

The electrode serves as a crucial conduit between the signal conditioning circuits and the uterus of pregnant women. The effectiveness of the device immediately influences the dependability and comfort of pregnant women while using it as well as the quality of the signals that are collected. Specific performance parameters must be met by the electrode in order for it to accurately and efficiently capture the foetal ECG signal and guarantee that it has a high signal-to-noise ratio (SNR). High-quality signal capture is possible thanks to the AgCl electrode's strong conductivity, low noise, and stable baseline.

The feasibility of creating a surface ECG vector map using three linearly independent ECG electrodes is examined. Three acquisition channels, a reference point, and a left leg drive are all part of the electrode placement's design. 5 cm below the centre of the pregnant woman's navel should be the reference electrode position. A triangle is formed around the navel by three acquisition electrodes. The participant's right side is where the left leg drive electrode is located. Because it maximises the SNR, this design was chosen [30].

Signal Acquisition Module;

Instantaneous high voltage may be produced during the recording of foetal ECG detection due to the influence of the outside environment, harming the hardware circuit as a whole. Additionally, there is a lot of electromagnetic interference present where the ECG acquisition equipment is used. A buffer is made to raise input impedance, boost load capacity, and reduce noise. The hardware acquisition system is simultaneously given a preprocessing circuit, which removes high-frequency interference and provides overvoltage protection, and is made up of a second-order passive low-pass filter and a limiting circuit. The fetal ECG signal is relatively weak, and the amplitude of the fetal ECG is varied from 10 µV to 60 µV. It is susceptible to maternal interference, myoelectric interference, and power frequency interference [31] . Because of this, the hardware acquisition system must have high input impedance, low noise, and a high common-mode rejection ratio (CMRR). This system's data acquisition module is built with an analogue front end ADS1299 (Texas Instruments, Dallas, TX, USA), which has a high-precision analogue to digital converter (ADC), programmable gain amplifier (PGA), and right leg drive (RLD). The ADS1299's 1 Vpp input referred noise, 1000 M input impedance, and 110 dB CMRR all meet the criteria of the acquisition system. The common-mode interference caused by the power line or other interference sources frequently affects the AECG collection process. The common-mode voltage is cancelled, the displacement current is decreased, and the common-mode interference is effectively suppressed when the RLD circuit recognize the common-mode component in the input signal and feeds it back to the human body. The microcontroller unit (MCU) of the monitoring system is an STM32F103 chip. The chip features a high working frequency of 72 MHz, single-cycle multiplication instructions, and hardware partition instructions. It also uses very little power (0.19 mW/MHz), and it has a wide range of peripherals.

Extraction of FECG signal;

It should be possible for the wearable device to extract the FHR trace and choose the recording channel with the most trustworthy FECG trace and best SNR. An algorithm for separating the foetal ECG from the maternal ECG should be put into place before choosing among the 8 channels.

Over the years, a number of FECG extraction techniques have been developed. techniques utilising adaptive filtering[32] ,averaging[33] and subtracting[34], have recently been defeated by the approaches of independent component analysis (ICA) and principal component analysis (PCA)[35,36]. We suggest utilising the non-blind method created by S. Martens et al., as stated in this methodology has two significant advantages over others: I robust in FECG detection; and ii) not computationally heavy and implementable on an FPGA board. In order to identify the maternal QRS peaks, this method relies on Principal Component Analysis (PCA). Averaging N prior MECG complexes results in the construction of an average MECG complex after the detection of maternal QRS peaks [37] .

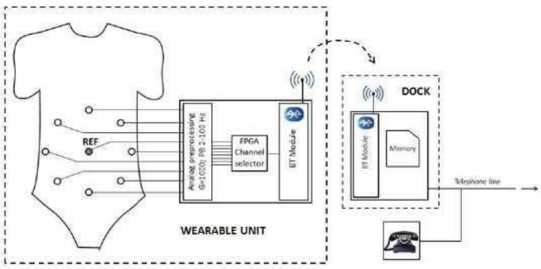

Fig. 2 shows a schematic depiction of the foetal monitoring device used at home. It is distinguished by a wearable device and a docking station. With the reference located in the navel, the wearable device is an 8-channel ECG recorder. The signals are processed analogly in the first stage (PB 2-100Hz, G = 1000), the FPGA extracts the FHR series, chooses the channel with the best information content, and then sends the signals to the dock via Bluetooth. The recordings are kept on a memory by the dock and sent to the hospital over the phone line. The average MECG template is scaled down to create the FECG, which is then subtracted from the real MECG complex. Finding the least-mean-square error between the MECG template and the real MECG complex is the basis of the scaling technique. The technique has been initially constructed and tested using Matlab® software. For a more thorough description of the algorithm, please see there.

Algorithm for Signal Analysis

Three steps make up the framework of the suggested strategy used in this work: (1) Pre-processing of signals. The AECG signals are processed to remove these erroneous values using the spline interpolation technique; signal quality assessment (SQA) for AECG to obtain a better-quality signal based on SampEn; and signal noise cancelling (SNC) for AECG by removing power line interference, baseline drift, and impulsive artefacts based on Notch filter, Butterworth filter, and median filter, respectively. (2) MECG subtraction is combined with a source separation method to obtain the FECG signal. (3) An algorithm for detecting foetal QRS complexes is applied to the filtered residual signals that still contain the FECG signal. Figure 3 displays the structure block diagram of the fQRS location using the algorithm suggested in this paper.

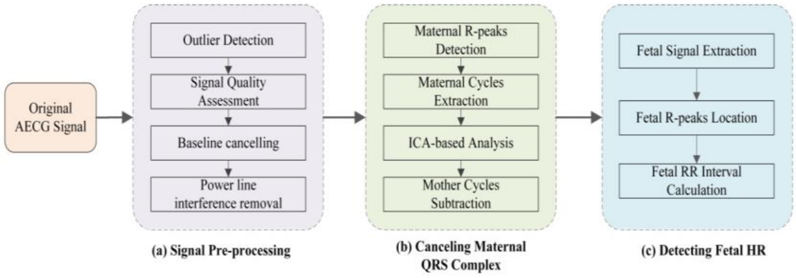

Figure 3. The Structure Block Diagram Of The Fetal ECG Extraction And Fqrs Location Using The Algorithm Proposed In This Work. (A) Signal Pre-Processing. (B) Canceling Maternal QRS Complex. (C) Detecting Fetal HR.

Also used in this work is another dataset from the PhysioNet/Computing in Cardiology Challenge 2013 Database (PCDB)[38]. 447 recordings from five separate databases make up the PCDB. The training set A consists of 75 AECG recordings. There are four channels of AECG signals in each recording, which lasts 60 seconds and is sampled at 1 kHz with a 16-bit resolution. Experts create reference annotations based on direct FECG data acquired from foetal scalp electrodes.

Signal Noise Canceling
Baseline drift, impulsive abnormalities, and power line interference are frequently present in the original AECG signals. Signal quality is greatly impacted by a sinusoidal component of power line interference that occurs at a frequency of about 50 Hz. Baseline drift, which can be seen in a lot of AECG data, is mostly brought on by human movement and breathing. The analysis and processing of the signal are adversely affected by these disturbances. In this study [39], the power line interference is eliminated using the notch filter. To get rid of baseline drift and impulsive artefacts, a Butterworth filter and a median filter are combined. After the signal noise-canceling stage, the AECG's power line interference, baseline drift, and impulsive artefacts are mostly gone.

Mother Cycles Subtraction
Maternal ECG (MECG), a significant component of the AECG signal, is well recognised to obscure foetal ECG signals. The MECG signal must therefore be effectively cancelled. Without knowledge of the transmission channel's parameters, blind source separation (BSS) refers to a method for separating or estimating the source waveform from the sensor array. The independent components of the original signal can be found in the multi-channel AECG signal since the BSS approach presupposes that the source signals are statistically independent. One of the ways for blind source separation that is frequently used and one of the most promising at the moment is the independent component analysis (ICA) approach. The ICA method is capable of eliminating the high-order statistical correlation in the observed signal by achieving the maximum value of the objective function of a certain contrast function and realizing blind source separation [40] .

Fetal QRS Complex Detection
The estimation and accurate identification of foetal QRS complexes may be hampered by the residual signal's potential presence of residual noise components. In this study, the noise components of the FECG signal are eliminated using the wavelet adaptive threshold de-noising approach. This procedure can successfully eliminate noise and produce a cleaner FECG waveform. The JADE algorithm is used in the interim to process the residual signal. The FECG signals show improved and more distinct peaks as a result of the JADE algorithm implementation, which helps in foetal QRS detection. The power of the foetus complex is still tiny and combined with residual noise, resulting in a poor SNR, despite earlier procedures removing noise and artefacts. The criteria for a priori selection of the most effective channel for foetal ECG detection become less reliable as a result. The retrieved foetal ECG components are used for the foetal QRS complex localization step. An adaptive threshold of derivative amplitude is used to detect foetal QRS complexes; it is automatically initialised and recursively adjusted with each new detection [41]. The weighted derivative signal's greatest value is what the algorithm looks for. In order to improve the samples near the projected site of the QRS complex, the weights are specified by the trapezoidal window. On all channels, the fQRS complex detection method is used. In the end, the best fQRS estimate is chosen based on the prior understanding of typical foetal RR values.

EXPERIMENTS AND RESULTS
Experiment Design;
The three subjects in this work are from the First Affiliated Hospital of Nanjing Medical University. The detailed demographic information of this experiment is presented in Table 1. Additionally, informed consent is obtained from each pregnant woman in this experiment. The subject experimental protocol is approved by the Ethics Committee and the study number is 2020-SRFA-183.

Statistical Information	Age (Years)	Height (cm)	Weight (kg)
Average	29	159	65
Standard Deviatition	1.8	1.2	5.4

Table1. The Detailed Demographic Information Of The Subjects In This Experiment.

To confirm that the suggested monitoring system can measure foetal signals in various states, including supine, seated, and standing postures, the experiment is set up in a laboratory environment that is analogous to a home environment. Three steps make up this work's experiment protocol. First, expectant mothers are instructed to remain supine for four minutes. The next two minutes are spent having the subjects sit and observe AECG signals. Last but not least, the subjects stand up and are observed for an additional two minutes. The expectant mothers are about 37 weeks along.

EvaluationPerformance

To evaluate the error of fQRS complexes detection in the context of NI-FECG extraction, a matching window of 50 ms is utilised, with each foetal QRS site labelled by experts as a centre [42]. It shows that the detected fQRS is the right value if the location of the detected fQRS is in the matching window. According to the ANSI/AAMI guidelines, which are as follows, the performance of this study is assessed in terms of sensitivity (Se), positive predictive accuracy (PPV), accuracy (ACC), and its harmonic mean (F1):

$$Se = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$PPV = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$ACC = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$

$$F1 = 2 * \frac{PPV * SE}{PPV + SE} = \frac{2\mathrm{TP}}{2\mathrm{TP} + \mathrm{FN} + \mathrm{FP}}$$

False Positive refers to incorrectly identified foetal QRS complexes, True Positive refers to the number of True Positives that match the foetal QRS complexes that experts have highlighted, and False Negative refers to False Negative results (missed detected foetal QRS complexes).

A straightforward and understandable technique to show data consistency is via a Bland-Altman graph. The Bland-Altman method's fundamental principle is to determine the mean difference between the two sets of measurement results and to use the 95% agreement limit as the mean difference (1.96 SD). The accuracy value of the foetal heart rate could therefore be further evaluated using the Bland-Altman plot. The suggested method's predicted foetal heart rate values will be compared to the reference annotations, and the 95% limit will be used to test for differences.

RESULTS

Our approach has been applied in MathWorks Inc.'s Matlab 2019b, which is available online. Eight AECG recordings (r01–r12) from three separate patients make up the dataset (DS-database) that was gathered for this experiment. Three 2-min long AECG signal channels totaling 3309 fQRS waves are included in each recording. The specialists produce the reference annotations. Figure 3 displays the patient A's AECG signal that was recorded while simulating a supine position. It is evident that the AECG signal's quality is good and that a distinct fQRS can be seen.

Figure 4. The Collected AECG Signal Of Subject A, Who Simulated Supine Posture (DS-Database). (A) AECG Signal With 120 S Length Interval. (B) AECG Signal With 5 S Length Interval.

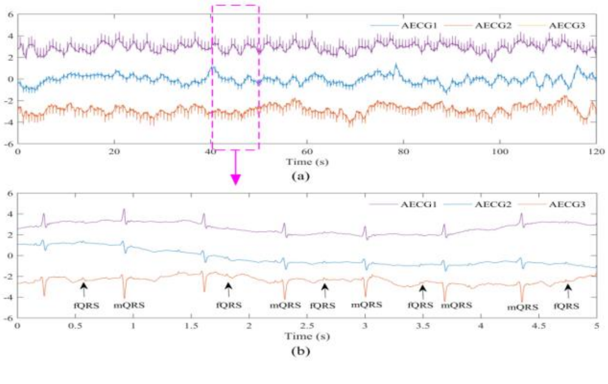

Figure 5 shows the original AECG recording and the filtered AECG after SNC. It can be seen that the AECG waveform becomes cleaner after this step. Part of the result of the extraction process of the MECG signal, mQRS location, fetal ECG signal, and fQRS location is shown in Figure 6. It can be seen that the MECG signal and FECG signal are well separated. An example result of mQRS and fQRS estimation using the proposed algorithm on the raw AECG signal is illustrated in Figure 6a. The figure manifests that the mQRS and fQRS wave positions are correctly located, respectively. A visual display of extracted MECG along with the result of mQRS location is exhibited in Figure 6b. In this Figure, we can see the complete MECG signal and correct mQRS position. In addition, the residual signal (i.e., fetal ECG signal) with the location of the estimated fetal R peaks and the truth value annotations of fetal R peaks by the experts is presented in Figure 6c. We are capable of obtaining that the estimated fetal R peak matches the reference annotation.

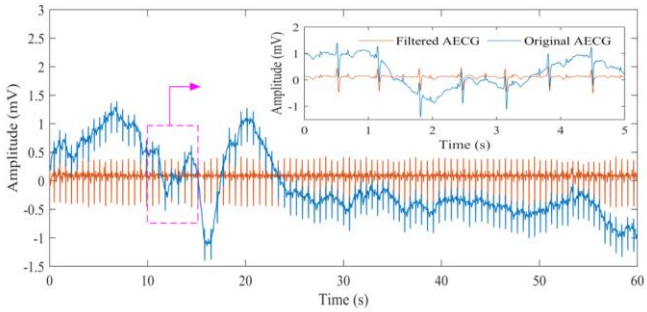

Figure 6. The Original AECG Recording And The Filtered AECG After SNC (DS—Database).

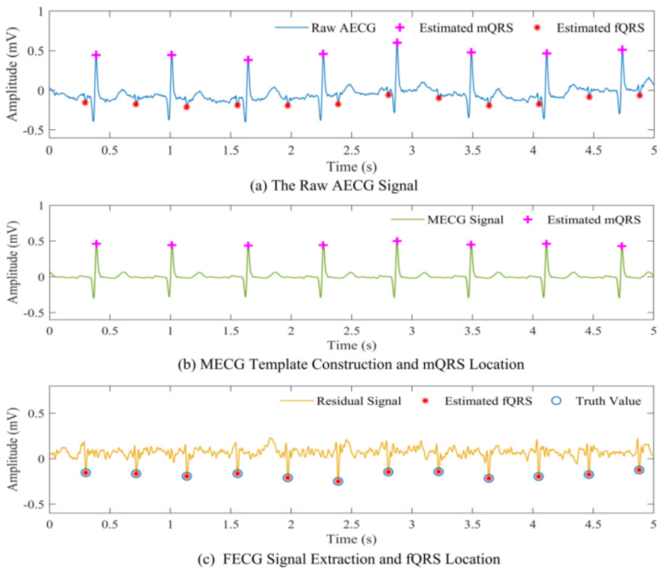

Figure 6. Part of the result of the extraction process of MECG signal, mQRS location, fetal ECG signal, and fQRS location (DS-database). (a) An example result of mQRS and fQRS estimation on the raw AECG signal. The '+' represents the mQRS location position, and the '*' represents the fQRS location position. (b) A MECG template signal is extracted and mQRS location on the extracted MECG signal. The '+' represents the mQRS location position. (c) A FECG template signal is extracted and fQRS location on the extracted MECG signal. The '*' indicates the fQRS location position using the algorithm, and the 'o' denotes the truth value annotated by the expert.

The Bland–Altman statistical analysis method for the estimated fetal heart rate values of the proposed method and the reference annotations (recording r02 and r09) is displayed in Figure 7. The results show that most of the values lie within the 95% interval for the recording of r02 and r09. Performance metrics of the fQRS detection using this method on the DS-database are summarized in Table 3. We can obtain the correct number of fQRS wave detections, and the number of errors detected for each AECG recording. The average diagnostic Se, PPV, ACC, and F1 score are 99.62%, 97.90%, 97.40%, and 98.66%, respectively.

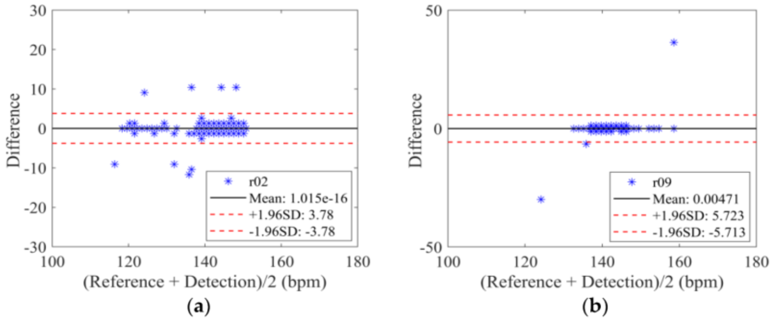

Figure 7. Bland-Altman Plot For Recording R02 And R09 Using The Proposed Method (DS-Database). (A) Bland–Altman Plot For Recording R02. (B) Bland-Altman Plot For Recording R09.

Table 2. Performance Metrics Of The Fqrs Detection Using This Method.

Subject	Recording	Position	TP	FP	FN	SE(%)	PPV(%)	ACC(%)	F1(%)
A	R01	Supine	282	3	1	99.65	98.95	98.60	99.30
	R02	Supine	281	0	0	100	100	100	100
	R03	Seated	280	1	0	100	99.64	99.64	99.82
	R04	Standing	260	15	7	97.38	94.55	92.20	95.94
B	R05	Supine	267	4	1	99.63	98.53	98.16	99.07
	R06	Supine	284	8	2	99.30	97.26	96.60	98.27
	R07	Seated	274	0	0	100	100	100	100
	R08	Standing	275	17	2	99.28	94.18	93.54	96.66
C	R09	Supine	275	2	2	99.28	99.28	98.57	99.28
	R10	Supine	271	3	2	99.27	98.91	98.19	99.09
	R11	Seated	273	4	1	99.64	98.56	98.20	99.09
	R12	Standing	269	14	0	100	95.05	95.05	97.46

Figure 8 displays the intuitive results of the Se, PPV, ACC, and F1 scores for all subjects in the supine, seated, and standing positions. The average Se, PPV, ACC, and F1 scores for spine posture are shown to be 99.52%, 98.82%, 98.35%, and 99.17%, respectively, with standard deviations of 0.28%, 0.82%, 0.96%, and 0.49%. The mean Se, PPV, ACC, and F1 scores for participants in the seated position were 99.88%, 99.4%, 99.28%, and 99.64%, respectively, with standard deviations of 0.21%, 0.75%, 0.95%, and 0.48%. The mean Se, PPV, ACC, and F1 scores in the standing posture are 98.89%, 94.59%, 93.60%, and 96.69%, respectively, with standard deviations of 1.35%, 0.44%, 1.43%, and 0.76%.

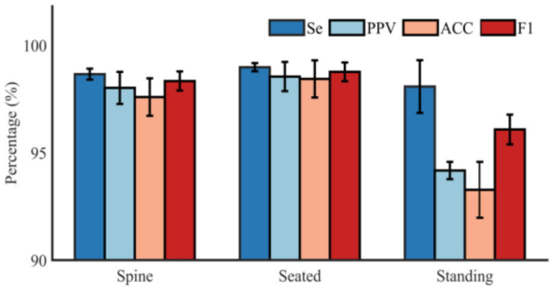

Figure 8. Intuitive Results Of *Se*, *PPV*, *ACC*, And *F*1 Score Of All The Subjects In Supine, Seated, And Standing Postures (DS-Database).

Positive impacts

1. To evaluate how women of child-bearing age perceive the use of remote fetal ECG monitoring technologies. Telemedicine has advanced to the forefront of healthcare delivery, including maternal–fetal medicine. Smart wearable electrocardiogram (ECG) devices can enable pregnant women to monitor their health and that of their fetuses. Such technology would be a logical extension of the telemedicine ecosystem.
2. The device is scientifically proven to monitor your and your baby's vital signs and development in real-time
In order to be effective, it has to be worn for at least 8 h during the night or during the day; it is most effective is worn continuously throughout day and night
3. Fetal heart rate monitoring may help detect changes in the normal heart rate pattern during labor. If certain changes are detected, steps can be taken to help treat the underlying problem. Fetal heart rate monitoring also can help prevent treatments that are not needed.
4. The safety of the Doppler ultrasound devices is stressed, in that they do no harm to the baby, but the risks of delaying seeking medical attention and the limitations of Dop- pler devices tend to be overlooked. Current practice Movements can vary considerably from fetus to fetus and at different times of the day.
5. The ECG is a very safe test and there are no issues with ECGs and pregnancy. The ECG does not involve any radiation or any chemicals into the woman's body.
6. A tocodynamometer uses high-frequency sound waves to measure your baby's heart rate. This fetal monitoring method is noninvasive and has no associated complications.
7. (ECG) is a test your healthcare provider uses to track your baby's heartbeat during labor or in the office. It provides real-time, continuous information about how your baby is doing through labor and delivery.

Negative Impacts

1. With internal monitoring, you may have some slight discomfort when the electrode is put in your uterus. Risks of internal monitoring include infection and bruising of your baby's scalp or other body part. Note: You should not have internal fetal heart rate monitoring if you are HIV positive.
2. In general, fetal heart rate monitoring is safe. But most experts believe that continuous monitoring isn't necessary for pregnancies at low risk of complications. Continuous electronic fetal monitoring can restrict your movement, which can be helpful during labor.
3. Stress-related changes in a pregnant woman's heart rate and blood pressure, along with chronic anxiety, can affect the heart rate of her developing fetus, a new study concludes.

4. Most of the time, heart palpitations during pregnancy aren't serious. They are a natural result of increased blood flow in your body. But you should tell your provider about heart palpitations, especially if they happen often. In rare cases, a serious health condition may be causing your symptoms.
5. One of the disadvantages of ECG is its associated increase in cesarean delivery rates. Patients should receive information on both intermittent auscultation and ECG to enable them to make an informed choice of method for intrapartum fetal assessment.
6. Decreased movement by the baby in the womb.
-Cramping.
-Vaginal bleeding.
-Excessive weight gain.
-Inadequate weight gain.
-The "baby bump" in the mother's tummy is not progressing or looks smaller than expected.

DISCUSSION

In this study, we create a portable, home-based FECG monitoring system for foetal and maternal health monitoring. To achieve the FECG waveform and foetal heart rate extraction, the ADT and ICA algorithms are combined. FECG signals can be captured by the Monica AN24 and Avalon foetal monitoring devices. However, due to the requirement for professional skills and knowledge to use the acquisition device [42] , those two technologies are not the most practical options for home-based monitoring. In contrast to the previously described home-based monitoring options, our FECG monitoring system has performed signal acquisition verification and foetal heart rate analysis in various positions (supine, seated, and standing).

It's important to note that in Figure 4, the displayed AECG signal allows us to clearly observe the FECG signal. The outcome shown in Figure 6, demonstrates that the extracted FECG signals from the gathered AECG signals are largely clear and interpretable, and can thus be a useful source of data for foetal health state monitoring. It must be underlined that an accurate morphological study of pregnant women and foetuses depends heavily on the quality of the AECG signal. As a result, it also suggests more stringent standards for the monitoring system's acquisition module. SampEn is also used to evaluate the AECG signal's quality in order to ensure the accuracy of the future signal analysis.

TABLE 2 exhibits that the diagnostic PPV, ACC, and F1 scores of r04 (standing) are, respectively, 94.55%, 92.20%, and 95.94%. R08 (standing) has a diagnostic PPV, ACC, and F1 score of 94.18%, 93.54%, and 96.66%, respectively. Additionally, r12 (standing) has diagnostic PPV, ACC, and F1 scores of 95.05%, 95.05%, and 97.46%, respectively. The relatively poor signal quality in the standing position may be the reason why the signal foetal R wave detection findings in the standing posture are worse than those in the supine and seated postures. Poor signal quality occurs when the foetus is standing because it has more room and time to move about.

TABLE 3 compares the results of the PPV, ACC, and F1 scores on the PCDB and DS-database comparing our work and other widely used methods. As can be shown in Table 4, the outcomes of this work outperformed the CNN, TS, AF, and FUSE technique approaches. In all AECG recordings from the DS-database, the proposed approach correctly recognises 3291 (TP) foetal QRS complexes and incorrectly detects 18 (FP) foetal QRS complexes, according to statistical analysis. According to the DS-database, the diagnostic Se, PPV, ACC, and F1 scores are 99.46%, 97.89%, 95.86%, and 98.67%, respectively. In addition, for all AECG recordings from the PCDB database, the suggested method correctly identifies 9210 (TP) foetal QRS complexes and incorrectly identifies 372 (FP) foetal QRS complexes. From the PCDB database, the diagnostic PPV, ACC, and F1 scores are 96.12%, 96.20%, 92.67%, and 96.16%, respectively. The results of the TS algorithm and FUSE method's foetal QRS detection are slightly lower than the average PPV, ACC, and F1 score from this study. The experimental outcome of this work, however, is much better than the CNN and AF approach's foetal QRS localization outcome. It also shows that the suggested method will significantly increase the accuracy of foetal QRS complex detection.

Table 3. Comparison Of Performance Metrics For Fetal QRS Detection Of Different Subjects In Different Methods.

Database	Approach	Se (%)	PPV(%)	ACC(%)	F1(%)
PCDB	CNN [24]	76	82	-	78.00
	TS[25]	-	-	-	93.90
	FUSE method [30]	95.90	96.00	-	0.9600
	This work	96.12	96.20	92.67	96.16
DS-Database	TS [25]	98.37	96.59	93.40	97.47
	AF[26]	90.18	92.87	86.69	91.51
	This work	99.46	97.89	95.86	98.67

Table 3. Comparison of performance metrics for fetal QRS detection of different subjects in different methods.

Although the adaptive filter method is theoretically more appropriate, the outcome is highly dependent on both the adaptive filter's configuration and the presence of a signal in the chest leads. Additionally, depending on factors like the mother's gestational week and the position of the foetus in the uterus, appropriate filter settings may change. The advantage of the non-adaptive method is that thoracic electrodes are not used; just abdomen electrodes are used. In our upcoming research, we'll concentrate on analysing foetal ECG signals and extracting R waves using a combination of adaptive and non-adaptive techniques. It is important to be aware that the hybrid method should be more effective at precisely extracting foetal signals and analysing them.

The current study has only evaluated short-term recordings in three different positions (supine, seated, and standing), and it has not been experimentally proven that consistent signal quality can be maintained during longer monitoring intervals. Furthermore, there aren't any power analyses done and there aren't many subjects.

CONCLUSIONS

In this study, we design a portable, home-based FECG monitoring application system that can be used to monitor pregnant women's health while they are lying down, sitting, or standing. The outcome shows that the AECG signal quality in seated and supine positions performs better than that of standing position. For improved FECG quality, the JADE method combines the ADT and ICA algorithms to extract the FECG signal, which can deliver an accurate and dependable FHR prediction. Medical resources and doctor time are contributed by the foetal health monitoring system. The system has several potential applications and is safe for expectant mothers.

To confirm the viability of the wearable foetal monitoring system in a 24-hour or long-term monitoring system, more participants' data will be collected in the future.

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