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A wearable system for in-home and long-term assessment of fetal movement

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Abstract

Objectives: This paper presents a novel wearable system for in-home and long-term fetal movement monitoring on a reliable and easily accessible basis.

Material and methods: The system mainly consists of four accelerometers for fetal movement signal acquisition, a microcontroller for signal processing and an Android-based device interacting with the microcontroller via Bluetooth Low Energy (BLE), providing the mother with information related to the fetal movement in an intelligible way.

Results: The proposed system can deliver reliable results with a specificity of 0.99 and a sensitivity of 0.77 for fetal movement time series signal classification.

Conclusion: The proposed wearable system will provide a good alternative to optimize the use of medical professionals and hospital resources, and has potential applications in the field of e-Health home care. Besides, the fetal movement acceleration signals acquired with volunteers (pregnant women) helps establish an initial database for future medical analysis of sensor-recorded fetal behaviors.

Keywords: fetal movements, wearable system, accelerometer, machine learning

1. Introduction and related works

Despite advances in science and technology, stillbirths are still a major problem around the world today [1]. Early detection of fetal compromise plays a key role in saving fetal life. Fetal movements in utero, which are early expressions for fetal neural activity, are positive indications of fetal well-being. It is important to know that a healthy baby should move regularly until into labor, and both change and disappearance of fetal movements could be an alarm to fetal compromise [2]. It is also observed that fetal movements are reduced in cases of placental insufficiency [3]. To save the fetus life in case of high risk pregnancy especially when placental insufficiency is long-standing, monitoring of fetal movements and early detection of fetal compromise has its greatest value in clinical medicine [4, 5].

Existing clinically available fetal movement monitoring methods include the following: 1) Ultrasonic technique, which is able to assess fetal well-being in a visualized way. Scanned movements may include truck, limb or head, and movements are documented as combined movements if they involve more than one fetal body part [6]. Ultrasound is usually regarded as the gold standard for fetal movement monitoring, but the disadvantage of this technology is that it is only accessible in a clinical setting, and an experienced clinician is needed to manipulate the ultrasound device. 2) Maternal perception of fetal movements, which is the oldest and most commonly used method to assess fetal well-being [7]. A pregnant woman may first feel her baby's movement from weeks 25 of the pregnancy or even a few weeks earlier. Compared to ultrasound, this method can be done at home, but the major drawback of this method lies on its subjectivity and imprecision. In the literature, it is reported that the sensitivity of maternal perception can vary considerably [6, 8]. Besides, in order to feel her babys activities, the mother has to keep quiet and stay still, causing a large impact on her daily routine.

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In recent years, with the advancement of microelectronic technology as well as the development in signal processing, automatic detection of fetal movements by using accelerometers and advanced signal processing technologies has gained a lot of attention [9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. When contacted with the maternal abdominal wall, a movement of fetal body parts with sufficient force generates vibrations that could be detected by one or a set of accelerometers placed on the surface of the abdomen. Accelerometers have promising characteristics such as small in size, low-price, non-invasive, high sensitivity and robustness, making them an ideal solution for fetal movement signal acquisition.

For automatic fetal movement monitoring based on accelerometer-recorded signals, some studies utilized threshold-based algorithms [15, 16, 17, 18], under the prerequisite that the mother keeps quiet throughout the measurement so that fetal movement signals are identifiable against ongoing low amplitude background noise. However, this approach may not reach a decent performance since it is highly sensitive to noises. In some other studies feature extraction was applied on the original acceleration signals to obtain information that was not readily available in the raw data. The concerned methods include statistical features in time domain [18] and time-frequency features [10, 16, 17, 19]. Then, based on the extracted features, signal classification was performed to identify fetal movement signals from other signals. One point worth mentioning is that some previously published papers proposed an additional sensor placed on the mothers thigh or back to detect and eliminate maternal artifacts [11, 14, 15]. However, until now there is still no standard for the optimal placement of this reference sensor, and the integration of this additional sensor involves additional complexity to the monitoring system and thus brings limits to the use of this technique in real world applications.

Despite promising achievements, most previously published works are still at a preliminary stage and are mainly focused on the processing of accelerometer-recorded signals. However, the usability of the fetal movement monitoring system still needs to be largely improved: when taking measurement, the mother is required to stay still and breathe quietly; sensors, wires and other electronic components are exposed outside; signal processing is performed by a computer with strong processing power or even by a professional signal analysis instrument, and so on. These limitations largely restrict previously proposed approaches from in-home and long-term assessment of fetal movement without affecting the mothers daily routine.

This paper presents a novel wearable system to address the usability issues. The system mainly contains: 1) four accelerometers for fetal movement data acquisition, 2) a microcontroller for data processing, 3) a well-designed garment which is adapted to the pregnant woman's morphology and 4) an Android-based monitoring device with a GUI (Graphical User Interface), interacting with the microcontroller via BLE (Bluetooth Low Energy) wireless communication and providing the user with statistical information related to fetal movements in an intelligible way. By fully integrating the embedded microcontroller and small-sized accelerometers into the garment, the portability and usability of the system is significantly increased, thus user experience and system acceptance could be largely improved. This paper is focused mainly on the hardware setup and fetal movement monitoring algorithm, and the design of the garment is not discussed.

The aim of the wearable system proposed in this paper is to provide an in-home and long-term solution for ensuring normal fetal development during pregnancy, to help optimize the use of medical professionals and hospital resources, and to constitute a good application for wearable sensors and systems in the field of e-healthcare.

2. Methodology

2.1. Hardware setup

The hardware of the wearable system is mainly composed of four tri-axial accelerometer sensors (NXP, MMA8451Q), a 32-bit high performance microcontroller (NXP, Kinetis KL16), a system-on-chip (Texas Instruments, CC2541) for BLE wireless data transmission and an Android Smartphone (Android Version: 8.0 Oreo) for information visualization. As shown in Figure 1, the main circuit containing the microcontroller and the BLE system-on-chip is packaged into a small portable box together with a battery ensuring the system fully operational for long-term measurements. A garment integrating all the embedded electronic components contains two belts with each one integrating two sensors. Further work involves the fully integration of the wires into the flexible and elastic fabric.
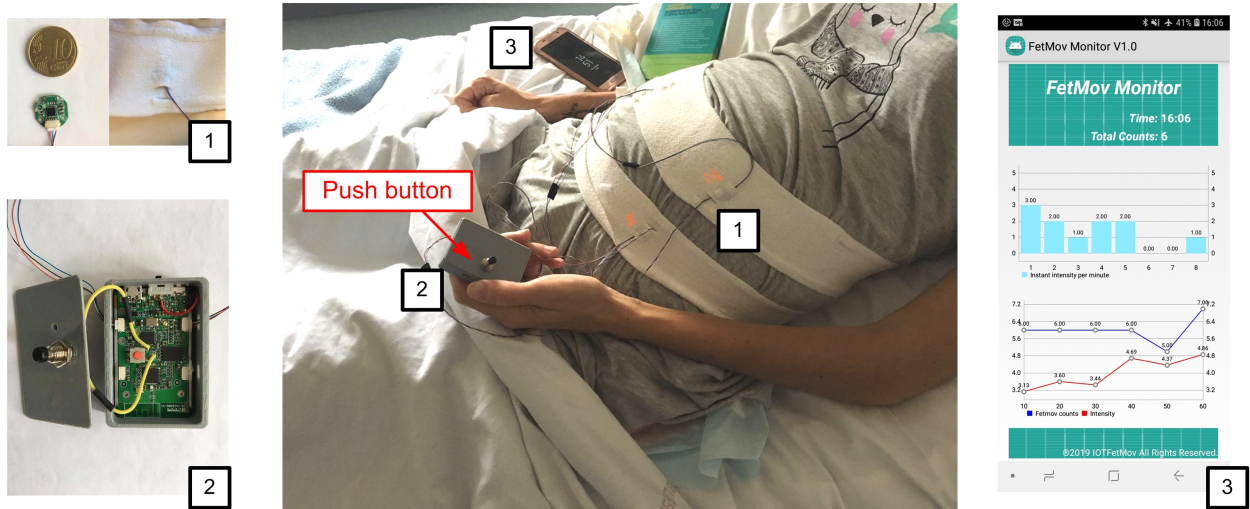
Figure 1: Experimental scenario of the proposed wearable system for fetal movement assessment, with close-up view of 1) the accelerometer sensor (totally 4 sensors are mounted on the system), 2) the main circuit board packaged into a small box, containing a microcontroller, a system-on-chip for BLE wireless transmission and a battery, and 3) the GUI of the Android monitoring device. For research proposes, one additional push button is added for the mother to record perceived fetal movements.

The measuring range of the accelerometer sensors is set to $\pm 2g$ ($1g = 9.81 \mathrm{m}/s^2$) and the sensitivity to 4096 counts/g since the output data have been transferred to numerical values via an integrated analog-to-digital converter (ADC). Signal transmission between the sensors and microcontroller is implemented with I^2C (Inter-Integrated Circuit) protocol. The sampling frequency is set to 60Hz.

For research purpose, one additional push button is added to the main circuit (see Fig. 1). During the experiment, the mother is requested to press this button when she perceives a fetal movement and hold it until the movement disappears. The push button signals can be used as a reference for labeling fetal movement signals among the ongoing acceleration data.

2.2. Algorithm for automatic fetal movement monitoring

In this section, a novel two-level algorithm for automatic fetal movement monitoring is proposed. Detailed explanation is given below.

2.2.1. First level: acceleration signal preprocessing

In order to eliminate interferences caused by sensor rotations, the magnitude of the tri-axial accelerometer data calculated using equation 1 is utilized for further analysis [13]. Acceleration magnitude signals are then filtered using an IIR (Infinite
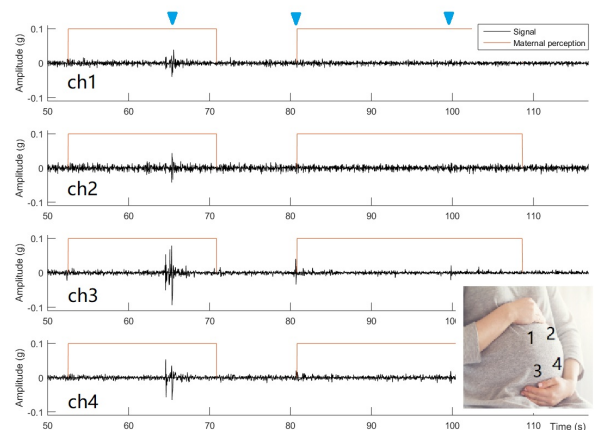

Figure 2: Acceleration signals acquired by four sensors with blue arrows indicating fetal movements, and maternal perception markers are plotted with red lines: when the button is pushed, the marker is triggered with the value other than 0. The signals have been preprocessed.

Impulse Response) band-pass filter with a bandwidth of [0.5Hz - 20Hz] in order to remove maternal respiration interferences (usually within 0.5Hz) as well as other high frequency noises. This setting is based on the previous findings in the literature

that the frequency spectral band of fetal movement signals is usually located below 20Hz [13, 19]. One example of four-channel acceleration signals after being preprocessed is shown in Figure 2, where the fetal movement signals are labeled by the maternal perception markers (red lines). It is observed that accelerometer-recorded fetal movement signals are often in the form of one or a series of spikes identifiable against other low amplitude background noises.

$$g[n] = \sqrt{x^2[n] + y^2[n] + z^2[n]} \qquad (1)$$

Maternal artifacts are one major challenge for the automatic detection of fetal movement signals. From Figure 3 it is observed that maternal body motion signals can mimic fetal movement signals, making fetal movement detection challenging. Besides, maternal heartbeat signals recorded by the accelerometers are also clearly visible but they are usually weak (with maximum amplitude of about 0.02g) compared to fetal movement signals.

2.2.2. Second level: signal classification based on features extracted from acceleration data

After preprocessing, acceleration signals are segmented into 4-second epochs without overlapping using a moving time window. Relevant features are calculated from each epoch and are then fed into a fuzzy ARTMAP classifier for further signal classification.

Feature extraction from data is significantly important for reducing the number of dimensions in original data vectors while not losing any useful information. However, finding a good data representation is very domain specific and is related to available measurements. On the one side, it is always better to be too inclusive rather than discarding any potential vital information [20], on the other side however, extracting high-dimensional features from raw data makes it challenging to be implemented in a microcontroller, due to its limited memory and restricted computational capability. In our research, potential informative features are listed first [21, 22], then feature dimensionality reduction is executed by utilizing Sequential feature algorithms (SFAs) and a Random Forest (RF) classifier. Feature dimensionality reduction helps to eliminate feature space redundancy and find the optimal feature subset, which is obtained using a wrapper method with the Forward Feature Construction. It starts with one feature only and pro-
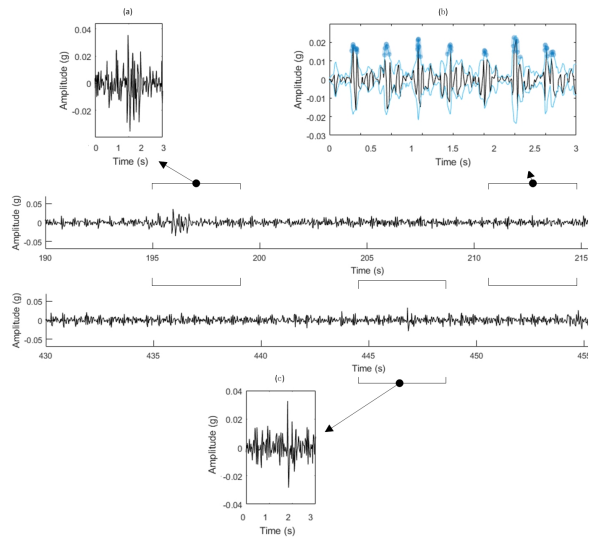

Figure 3: Three types of signals recorded by accelerometers, which are (a) maternal movement signal, (b) maternal heartbeat signal and (c) fetal movement signal, respectively.

gressively adds one feature at a time until the classifier reaches the highest classification performance. The performance of the random forest classifier is used for directing this search.

A fuzzy ARTMAP is then applied for signal classification and identification of fetal movements based on the extracted features. Based on adaptive resonance and fuzzy set theory, fuzzy ARTMAP is a lightweight machine learning algorithm different from other neural network-based algorithms. The most important advantage of using fuzzy ARTMAP is its easy implementation in a microcontroller [23]. Another advantage lies on its property of incremental learning, with which it can continuously update its parameters (e.g. weight vectors or topology) once new training samples are available without catastrophic forgetting of what it has learned before. More detailed description on the fuzzy ARTMAP algorithm can be found in [24, 25].

The architecture of the fuzzy ARTMAP is shown in Figure 4. It mainly consists of two fuzzy ART modules interconnected through the map field module F^{ab}. During the supervised training, the F_0^a layer in the ART_a module is fed with complement coded input vectors, and the ART_b module deals with the relevant correct prediction labels. If the prediction result given by ART_a based on input vector does not match the correct label given by ART_b,
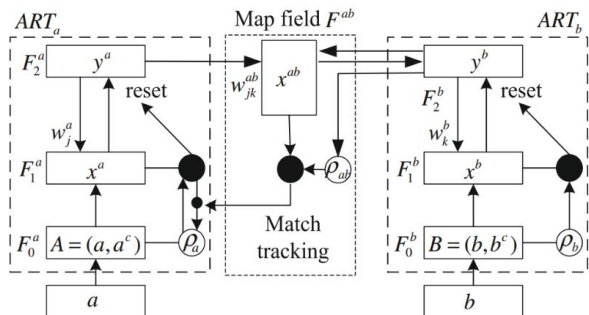
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Figure 4: Architecture of the fuzzy ARTMAP algorithm.

Table 1: Performance comparison of different wavelets on acceleration signal classification.

Feature space	Wavelet type	Accuracy
DWT	db1	0.966
	db2	0.967
	db6	0.962
	sym6	0.964
	sym10	0.954
	coif2	0.963
	coif4	0.959

match tracking will take place. Match tracking triggers ART_a to search for another category that correctly predicts the label given by ART_b or adds a new category in case if no existing categories matches. Selection of one category from F_2^a is done based on the category choice function 2.

$$T^j = \frac{|I \wedge \omega^j|}{\alpha + |\omega^j|} \qquad (2)$$

where I is the complement code of input vector, α is the choice parameter, ω_j is the weight of node j, and the fuzzy AND operator $\wedge$ is defined by equation 3.

$$(p \wedge q)_i = \lim(p_i, q_i) \qquad (3)$$

The node that with the highest category choice value in F_2^a is then tested with the vigilance value ρ according to the match criterion equation 4, if this condition is met, the parameter update is executed by equation 5.

$$\frac{|I \wedge \omega|}{|I|} \geq \rho \qquad (4)$$

$$\omega_j^{new} = \beta(I \wedge \omega_j^{old}) + (1-\beta)\omega_j^{old} \qquad (5)$$

where β is the learning rate with the range of [0, 1].

3. Experiment and results

3.1. Data acquisition

Fetal movement data acquisition was performed with 14 healthy volunteer subjects (pregnant women) from the 25th - 39th week of gestation. A wide range of gestation weeks was covered in order to collect different types of fetal movement signals. Only subjects with singleton pregnancy were considered. The average recording duration was about 15

minutes. During the measurement, the subject was asked to hold the push-button in the hand to record maternal perceptions.

Before starting the measurement, the pregnant woman was asked to locate the area on the abdomen where she felt the strongest fetal movements, and one belt was placed just above this area so that the most intensive fetal movement signals could be collected by the two sensors in this belt. However, the placement of the second belt varied according to the specific experimental requirements. For some measurements the two belts were placed next to each other to focus on the area where the most intensive movements were perceived by the mother. In other cases however, it was placed on the pregnant womans upper body (close to the breast) to record maternal heartbeat signals for future analysis of this artifact. A comparison of the system performance between these two experimental settings may also help to find out the most efficient way for multisensory fetal movement monitoring.

Besides, for some measurements, the pregnant woman was required to stay still in order to collect clean and undistorted signals without interferences caused by maternal body motions, while for other measurements the subject was allowed to move her body, talk or even walk. These activities were noted synchronously by an observer and were used for artifacts analysis. Artifacts were classified into maternal body motion, walking, maternal heartbeat and background noises, respectively.

3.2. Feature construction

Firstly, feature selection was done by listing potential informative features in both time domain and DWT domain. In order to investigate the
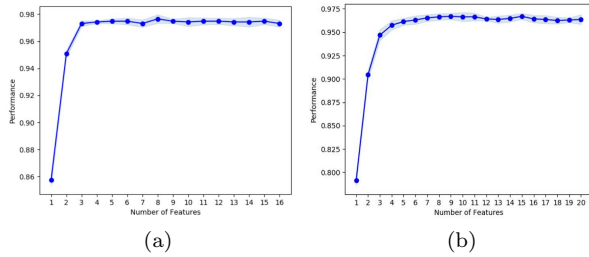
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Figure 5: Average classification performance on the training samples, with forward feature construction on time domain (a) and db2 wavelet (b).

performance of different wavelets on accelerometer signal classification, Daubechies wavelet db1, db2, db6, Symmlet wavelet sym6, sym10 and Coiflet wavelet coif2, coif4 were tested separately. The db2 wavelet which outstands among others was chosen (see Table 1). Feature dimensionality reduction was implemented in time domain and DWT domain separately, and the final optimal feature space was obtained by combining the optimal subsets in both time domain and DWT domain (see Figure 5). Since time domain features are computationally simple while the DWT represents signals energy distribution in frequency sub bands, combining these two feature spaces could help to improve the robustness and generalization ability of the fuzzy ARTMAP classifier.

3.3. Validation of the performance of the fuzzy ARTMAP classifier

70% of the entire samples (feature vectors extracted from the collected acceleration data) were used for training and the others used for testing. The confusing matrix of the classification results on testing data is shown in Table 2. From the confusing matrix it is observed that compared with the other artifacts, those caused by maternal body movements are relatively difficult to be distinguished from real fetal movement signals (with about 10% of the fetal movement signals misclassified as maternal body motion). The reason behind this is that some maternal body movements may cause abdominal deflections similar to those caused by a real fetal movement.

3.4. Classification specificity: a crucial factor

False positives (FP) in this study means that artifacts and other noise signals are misclassified by the classifier as fetal movement signals. High false positive rate (poor classification specificity) could cause a severe problem: the system may reassure the mother with the fetuss good health condition since it claims a normal detection of fetal movements which are actually composed of large amount of artifacts. However, the fetus's actual health status remains unknown. As a result, the baby's life could be put in danger because of delayed rescue. In our research, the proposed fetal movement monitoring approach was validated with an outstanding specificity of 99% and a sensitivity of 77%. Please note that the trained fuzzy ARTMAP classifier is able to give an "Unknown" classification output of a specific signal if the latter has never been learned before. Based on this setting, when excessive and complex artifacts are involved and many acquired signals are labeled as "Unknown" (which means that there may also be fetal movement signals but are probably distorted and overlaid), the system will launch an alarm to the mother asking her to keep quiet and stay still until the system receives enough clean fetal movement signals to carry on the necessary monitoring of her baby.

4. Limitation

In case of excessive noise interference, artifacts start to overlay useful signals, resulting a significantly drop on the SNR (Signal Noise Rate). A signal will be rejected without any analysis if it is labeled as "Unknown" by the system, leading significant information loss. This is the case when the mother is performing continuous activity for a long period of time, such as walking or running. To address this problem, further research will aim at blind signal separation (BSS) approach for separating useful signals from ongoing noisy signals. To do so, a prior knowledge on spectral distribution of fetal movement signals must be established in order to select useful ICs and to eliminate others. Another limitation of this paper lies on the absence of a trustworthy reference. Fetal movement signals for training the fuzzy ARTMAP classifier were perceived and labeled by the pregnant woman, which is subjective and imprecise. As a result, pseudo samples may be included into the training dataset, leading to a degradation of the classifier performance.

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Table 2: The confusion matrix of the classification results on test set. The acronym FetMov stands for fetal movement and BG stands for background noise.

		CLASSIFIED					
		Unknown	FetMov	Body motion	Walking	Heartbeat	BG
	Unknown	0	0	0	0	0	0
	FetMov	0	92	12	4	3	3
TRUTH	Body motion	0	5	103	0	0	0
	Walking	2	0	3	159	0	0
	Heartbeat	0	2	0	0	193	0
	BG noise	0	0	0	0	0	185

5. Conclusion

In this paper, a novel wearable system for long-term and in-home fetal movement monitoring is presented. By integrating electronic components in a garment, the portability and usability of the system is largely increased. An android-based device is developed for providing the user with information related to fetal movements in an intelligible way. A two-level approach implemented into the wearable system is presented for online and automatic monitoring of fetal movements based on accelerometer-recorded data. Experimental results proved that the proposed system has a decent performance for detecting fetal movements among other artifacts. Besides, fetal movement acceleration data collected from real volunteers (pregnant women) helps to establish an initial database for a specific medical analysis of sensor-recorded fetal behaviors. The proposed system can be a good alternative to reduce unnecessary use of specialists and hospital resources and has potential applications in the field of e-Health home care.

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