NON-INVASIVEMONITORING OF FETAL MOVEMENTS USING TIME-FREQUENCY FEATURES OF ACCELEROMETRY

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ABSTRACT

This paper presents a time-frequency approach for fetal movement monitoring which is based on the instantaneous amplitude (IA) and instantaneous frequency (IF) of signals collected using 3axial accelerometers placed over the maternal abdomen. Results of a feature selection method based on receiver operating characteristic analysis shows that the mean of the IAs and deviation of the Ifs outperform other features. A support vector machine based classifier which uses these 2 features exhibits a total accuracy of 96.6% with reasonably high sensitivity and specificity.

Index Terms - Fetal Movement, Accelerometry, Instantaneous Amplitude, Instantaneous Frequency, Support Vector Machines.

1. INTRODUCTION

Medical professionals still face significant difficulties in monitoring fetal wellbeing. Traditional methods of fetal monitoring rely heavily on the professional's ability to receive and to process the sensory information. Advanced methods such as Doppler shift Cardiotocography (CTG) and Ultrasonography (US), on the other hand, examine the foetus for a short period of time (e.g. 20 minutes) which of necessity limits the capacity to observe time based changes in fetal status [1].

Despite the increasing use of CTG, Ultrasound, and hormone measurements, there is good evidence that the rate of still birth has remained fairly constant [2]. Accordingly, to improve fetal surveillance, development of recording techniques to study fetal behaviour over more prolonged periods is necessary. Fetal movement (FetMov) which is synonymous with fetal life can be assessed for prognostic and diagnostic aims in pregnancy supervision [3, 4]. These movements are spontaneously generated by the central nervous system [3] and can be monitored for both immediate well-being and prenatal causes of childhood disabilities by giving an insight to the neurodevelopmental status of the foetus [5].

FetMov can be monitored using active and passive methods [6]. Active methods such as US which introduce

energy into the foetus cannot be used for long term monitoring. Passive techniques which use fetal generated signals to detect FetMov non-invasively are realized using a variety of mechanical/electrical transducers.

Several passive methods use the pressure waves generated by the foetus in its surrounding fluid to detect FetMovs. Each transducer uses a different feature of the displacement resulting from this pressure wave. Strain gauge and piezoelectric sensors correspond to the amplitude of displacement to generate the output electrical signal. The signal that resulted from inductive sensors is proportional to the speed of displacement and in the case of accelerometer; it is the acceleration of displacement which is considered for generation of the electrical output signal.

We used solid state versatile accelerometers transducers that are used in applications such as measuring gravity, body movement, along with gyroscopes in inertial guidance systems, and in airbag deployment systems for cars. They consist of a suspended cantilever beam (also known as seismic mass) with some type of deflection sensing and circuitry. Recent advances in semiconductor technology has provided new accelerometers that are small, low powered, sensitive, and robust enough to be proper to be employed in long term monitoring systems.

Although accelerometry data has been previously applied for FetMov monitoring, little work has been done on developing automatic signal processing algorithms for detection or classification of FetMovs. Previous studies [6, 7] used the root mean square (RMS) value of the sensors magnitude to detect FetMov in 3 datasets which resulted in an average sensitivity of 60%. A more recent study [8] proposed a time-frequency approach for FetMov detection by using of accelerometry data. The study used time-frequency matching pursuit and time-frequency matched filter decomposition of 6 datasets of FetMov and achieved an average of 84% true detection rate. Although this method is shown to work for this purpose, it is computationally intensive. The method we propose in this paper extracts time-frequency based features directly from the signal and therefore is computationally more efficient than other time-frequency based methods.

2. DATA ACQUISITION

The setup used for recording FetMov in this study uses 3 parallel recording systems and is illustrated in Figure 1. The first is the accelerometry system which is composed of four 3-axial accelerometers (ADXL330, Analog Devices [9]) connected to data acquisition platform (ADInstruments, Sydney, Australia) and then to a laptop computer running PowerLab, the data acquisition software. One sensor (sensor No.4) is located on mother's chest and used for identifying maternal artefacts. The other three sensors were mounted on the mother's abdomen using adhesive tape. To reduce maternal artefact effects, mothers were asked to remain still and an observer noted specific maternal activities such as talking, laughing, and coughing.

An ultrasound imaging system (either a GE Voluson 730 Expert with a GE AC 2-5MHz probe or a GE Voluson E8 with a GE RAB 4-8MHz probe) was used at the same time as the accelerometry system to act as the reference signal. Ultrasound videos were recorded and later marked by a trained clinician to indicate the onset and offset of movements. A handheld toggle which generates triggers was used to record maternally perceived FetMovs. The accelerometry signals were collected at the sampling rate of F_s =100Hz. Data recorded from 11 pregnant women were used.



Figure 1 – Fetal movement data acquisition setup [8]

3. METHODOLOGY

3.1. Data Analysis

Typical signals from the accelerometry system are depicted in Figure 1. The red arrows indicate places where a movement has occurred. The output of the kth sensor is comprised of three voltage signals proportional to the acceleration in direction x, y and z and are respectively called $x_k[n]$, $y_k[n]$, and $z_k[n]$. Before starting the main procedure, data analysis was performed to determine the frequency band in which most of the power of the FetMov signals reside which was found to be 0.5-45Hz.



3.2 Feature extraction

The methodology used for feature extraction and selection is shown in Figure 5(a). First the magnitude of each sensor is found using:

$$A_k[n] = \sqrt{x_k^2[n] + y_k^2[n] + z_k^2[n]} \quad for \ k = 1,2,3,4 \quad (1)$$

This is because the sensor magnitude indicates the original acceleration direction and is directly proportional to the force generating the movement [9]. Thus the presence of movements can be seen more effectively in sensors' magnitudes. The magnitude signals are then band-pass filtered between 0.5 and 45Hz based on the result of data analysis. In the next step, features are extracted from the instantaneous amplitude (IA) and instantaneous frequency (IF) of the filtered signalS_k[n]. If we denote $Z_k[n]$ as the analytic associate of $S_k[n]$, i.e.:

$$Z_k[n] \triangleq S_k[n] + jH[S_k[n]] = a_k[n]e^{j\phi_k[n]}$$
(2)

Where $H[\cdot]$ the Hilbert is transform operator, then $a_k[n]$ is the IA of the signal $S_k[n]$.

The IA of the reference sensor No. 4 is only used for detecting and removing maternal artefact and not considered for feature extraction. A non-uniform thresholding based on the histogram of $a_4[n]$ (the IA of the reference sensor) was used to remove segments with their IA >95th percentile.

The IF of $S_k[n]$ was estimated using the Real Base-Band Delay Demodulator method as follows. First $Z_k[n]$ is normalized:

$$Z_{kn}[n] = \frac{Z_k[n]}{|Z_k[n]|} = Z_{knr}[n] + jZ_{kni}[n]$$
(3)

Then the IF is computed as:

$$f_k[n] = \frac{F_s}{2\pi} \arcsin(h_k[n]), \tag{4}$$



Figure 3 – Magnitude of the signals of Figure 1

where

$$h_k[n] = Z_{kni}[n]Z_{knr}[n-1] - Z_{knr}[n]Z_{kni}[n-1]$$
 (5)

Finally, for each sensor, the mean, standard deviation, and deviation of its IA and IF are calculated, using the following equations, as potential features.

$$F_1^{(k)} = \frac{1}{N} \sum_{n=1}^{N} a_k[n]$$
(6)

$$F_2^{(k)} = \left[\frac{1}{N} \sum_{n=1}^{N} \left[a_k[n] - \overline{a_k}[n]\right]^2\right]^{1/2}$$
(7)

$$F_3^{(k)} = max[a_k[n]] - min[a_k[n]]$$
(8)

$$F_4^{(k)} = \frac{1}{N} \sum_{n=1}^{N} f_k[n]$$
(9)

$$F_5^{(k)} = \left[\frac{1}{N} \sum_{n=1}^{N} \left[f_k[n] - \bar{f}_k[n]\right]^2\right]^{1/2}$$
(10)

$$F_6^{(k)} = max[f_k[n]] - min[f_k[n]]$$
(11)

In (6)-(11), $F_l^{(k)}$ denotes the l^{th} feature extracted from the k^{th} sensor. We therefore obtained 6 features for each sensor.

3.3 Feature fusion

Feature fusion is achieved by combining the extracted features from all 3 sensors. In this study, two feature fusion methods are investigated. In the first method the RMS of the features and in the second one the mean of the features, as given below, were used:

$$Frms_{l} = \sqrt{\frac{1}{3} \sum_{k=1}^{3} [F_{l}^{(k)}]^{2}} \qquad l = 1, 2, ..., 6 \qquad (12)$$

$$Fmen_{l} = \frac{1}{3} \sum_{k=1}^{3} F_{l}^{(k)} \qquad l = 1, 2, ..., 6 \qquad (13)$$

For example, *Fmen*₆ is the mean of the deviation of the IFs extracted from the 3 sensors:

$$Fmen_{6} = \frac{1}{3} \sum_{k=1}^{3} max [f_{k}[n]] - min [f_{k}[n]]$$
(14)

3.3 ROC analysis and feature selection

In order to evaluate the performance of each of the 12 combined features, i.e. $Frms_l$, l = 1,2,...,6 and $Fmen_l$, l = 1,2,...,6, detecting FetMovs, its receiver operating characteristics (ROCs) was found by varying the feature threshold and the area under ROC curve (AUC) calculated [10]. The ROC of a feature is a plot of its sensitivity versus 1-specificity and the AUC is a measure of how well the feature can discriminate between FetMovs and background segments. A feature with an AUC value of 1 is a perfect one and AUC value of 0.5 corresponds to a random–guessing feature. Features with higher AUCs are nominated for classification purpose.

3.4 Classification

A vector containing the selected features was used to train a support vector machine (SVM) with polynomial kernel. SVM is a non-probabilistic binary linear classifier which constructs a hyper-plane in the space spanned by the feature vectors. The classifiers based on SVMs are trained quickly and their performance is insensitive to over-training [11].

4. EXPERIMENTAL RESULTS AND DISCUSSION

4.1 ROC analysis results

A database containing the accelerometry data acquired from eleven subjects were used for evaluating the performance of the proposed features. In this study, 1507 non-overlapping FetMov segments and 1725 non-overlapping background segments were extracted randomly from 349 min of recordings. The FetMov segments were cropped using the US mask and background segments were extracted from sections which contained no movement and no artefact. All these segments were used for ROC analysis as depicted in Figure 5(a). For the l^{th} feature, $F_l^{(k)}$; k = 1,2,3 is calculated using the corresponding formula given in Eq. (6)-(11). The features are then combined using Eq. (12) and Eq. (13). Finally, the ROC analysis is performed on **Frms**_l and **Fmen**_l and the resulting AUC is calculated. For illustration, the ROC of **Fmen**₆ is depicted in Figure 4.



The AUC values for all features with different fusion methods are given in Table 1. All features perform well except F_3 , i.e. the deviation of the IA of the sensors. Based on the results of ROC analysis, the mean of the IAs and deviation of the IFs were selected as the best performing features and mean function was chosen for combining the features, i.e. **Fmen**₁ and **Fmen**₆.

Table 1- AUC values relating to different features

feature Fusion method	F ₁	F ₂	F ₃	F ₄	F ₅	F ₆
RMS	91.68	83.32	56.59	91.06	88.30	99.27
Mean	91.92	83.06	56.64	92.4	89.32	99.27

4.2 Classification results

This study used a classification methodology based on the SVM which is shown in Figure 5(b). Once the IAs and IFs of the signals are estimated, based on the results presented in Table 1, the mean of the IAs and deviation of the IFs are calculated. These features are combined using the mean function. These 2 features form the feature vector which is fed to the SVM for classification. 20% of the data was used for training and the remaining for testing. The classification was performed using Sequential Minimal Optimization method with a polynomial kernel function of order 8.

The statistical parameters of the classifier; namely: its sensitivity, specificity, and total classification accuracy are given below.

$$Total \ accuracy = 100 \times \frac{TP + TN}{TP + TN + FP + FN} = 96.64\%$$
$$Sensitivity = 100 \times \frac{TP}{TP + FN} = 97.96\%$$
$$Specificity = 100 \times \frac{TN}{TN + FP} = 95.47\%$$

where TP, TN, FP, and FN stand respectively for true positive, true negative, false positive, and false negative.

5. CONCLUSIONS

Accelerometry data recorded for detecting fetal movements can be accurately classified using time-frequency based features extracted from the IAs and IFs of the signals. The proposed classification method based on the SVM which uses only 2 features, i.e. the mean of the IAs and deviation of the IFs, achieved a total accuracy of 96.64% with high sensitivity and specificity.

Future necessary work includes investigating the performance of other time-frequency based approaches such as those presented in [12-14], and also applying the proposed methodology to continuous recordings and comparing with results presented in [8]. Effective methods for artefact removal are required as artefacts and real FetMovs have similar patterns in some cases. Since the physical source that generates movements is different from that of the artefact, techniques such as blind source separation and direction of arrival estimation maybe useful as reported in [15].



Figure 5– The methodologies used in this study for a) feature extraction and selection, and b) classification.

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7. REFERENCES

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