Standardized Fourth Central Moment Based Three Step Algorithm for Fetal Movements Identification

Samitha Gunarathne
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
samithalg@eng.pdn.ac.lk

Thanushi Withanage
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
thanushiwithanage@eng.pdn.ac.lk

Upekha Delay
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
delayuh96@gmail.com

Thoshara Nawarathne
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
thoshara.nawarathne@eng.pdn.ac.lk

Roshan Godaliyadda
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
roshangodd@ee.pdn.ac.lk

Parakrama Ekanayake
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
mpb.ekanayake@ee.pdn.ac.lk

Janaka Wijayakulasooriya
Department of Electrical and Electronic Engineering
University of Peradeniya
Peradeniya, Sri Lanka
jan@ee.pdn.ac.lk

Chathura Rathnayake
Department of Obstetrics & Gynacology
University of Peradeniya
Peradeniya, Sri Lanka
chathura67@hotmail.com

***Abstract* — Fetal movement monitoring, one of the simplest methods of accessing fetal health lacks extensive studies beyond ultrasound or MRI scans, which are mainly conducted in a clinical setting. This study presents an algorithm which could identify fetal movement count using accelerometric data to measure the fetal well-being. The three-step algorithm includes a preprocessing step using kurtosis, Non-Negative Matrix Factorization followed by spectral clustering. It can be observed that this algorithm has the capability to differentiate fetal kicks from other artefacts with 96.55% accuracy.**

Keywords — Fetal movement, kurtosis, NMF, Spectral Clustering

I. Introduction

There is a limited number of methods practiced in gynecology to assess fetal health. One of the most common practices is to perform ultrasound scans. However, the long-term effects of ultrasound exposure have not yet been evaluated through generations. Hence it should be used with caution [1]. Another practice is to conduct a MRI scan. Both of these can only be conducted in a clinical setting and several restrictions are present [2]. Therefore, these types of scans are conducted scarcely throughout the pregnancy. Hence there is a huge vacant space for self-monitoring and practical systems to access the fetal well-being.

Fetal kick count is a standard procedure recommended by professionals to keep track of well-being of the fetus [3]. There are several recorded instances where a reduced number of fetal movements has been a prior indication of stillbirths and other adverse effects [4]. A standard practice is for the pregnant mothers to count the fetal movements themselves and notify their obstetrician of any change in pattern. Even though this practice has been done for a long time it is not the most reliable method available [5]. Studies have shown that the sensitivity of each mother in identifying fetal movement differ from each other. Also, trying to manually monitor the fetal movement pattern can cause psychological distress in mothers. For these reasons, it is mandatory to have a rudimentary approach to access these fetal kicks without any human intervention.

In current literature, there have been several attempts to recognize these fetal kicks using most elementary machine learning techniques [6][7]. In several types of research, they have extracted accelerometric signals corresponding to fetal kicks as felt by the surface of the pregnant mother's abdomen and implemented different algorithms such as threshold-based methods and time-frequency domain analysis. However, some algorithms failed to yield a satisfactory accuracy, while some algorithms proposed were too complex for standard commercial use. [8][9].

II. Objectives

In this research our intention is to produce a model where machine learning techniques like non negative matrix factorization and spectral clustering are applied to accelerometric signals which are extracted from mothers abdomen in an non-invasive manner. From that we aim to generate an optimum algorithm in order to generate a highly accurate and effective fetal movement detection method which will be helpful for pregnant mothers as well as doctors to ensure the well-being of the fetus.

III. Methodology

In this paper, we utilized the data set Fetal Movement Detection Dataset Recorded Using MPU9250 Tri-Axial Accelerometer [10]. This dataset includes observations from 13 pregnant mothers. The data was collected using the sensor MPU9250. It consists of raw time-domain data from a triaxial accelerometer and a triaxial gyroscope. Also, the instances a fetal movement occurred and the instances where other artefacts such as mother’s laugh occurred were noted.

The gyroscope measures the rotational motion in three principal axes where the accelerometer measures the incident acceleration or the vibration along each axis.

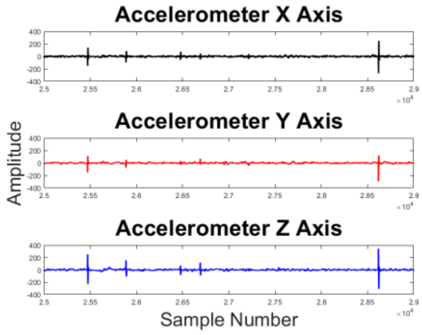

Fig. 1. Accelerometer data along three axes

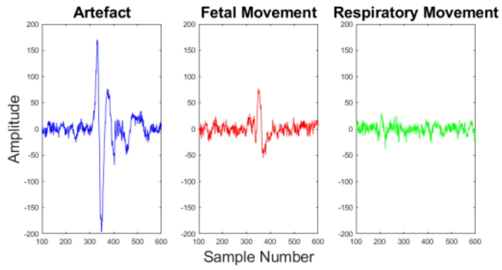

Fig. 2. Realization of artefact, fetal movement, and respiratory movement

Since the type of movement, we are attempting to classify is a fetal vibrations incident on the mother's abdomen it was decided to use the data from the accelerometer to develop the algorithm. The acceleration along three principal axes for few realizations are shown in Fig. 1.

It can be observed in the figure that the impact of fetal movement on Z-Axis is significantly more notable than the effect on other axes. Hence it was decided to use the data along the Z-Axis to conduct analysis. As it can be observed in Fig. 1, The signal is highly random with fetal kicks, mother's breathing movements and other artefacts from the mother's bodily movements. Due to these reasons, our primary focus was to develop an algorithm to classify the signal segments into three classes. They are fetal movements, other artefacts and mothers respiratory movements. For this initially, the raw signal was split into small realizations assuming the data given in the dataset to be the ground truth about the occurrence of fetal movements and other artefacts. A single realization of each class is shown in Fig.2.

When analyzing each realization initially the Short-Time Fourier Transform was applied. Then Non-negative Matrix Factorization was used to reduce the dimensionality of the data. This is done to reduce the computational power used. In general, a non-negative matrix can be represented as a multiplication of two low rank non negative matrices by utilizing Non-negative Matrix Factorization [11]. The matrix decomposition of Non-negative Matrix Factorization is shown in "Equation 1".

$M \approx AS$; where $M, A, S > 0$ (1)

M M : Input Spectrogram A A : Bases Matrix

S S : Abundance matrix

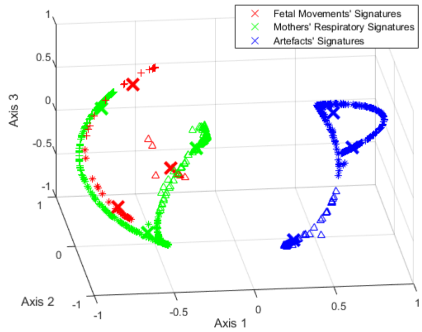

Fig. 3. Cluster signatures obtained after the two-step method

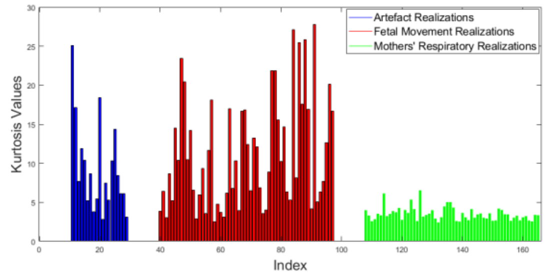

Fig. 4. Kurtosis values obtained for each realization

The resulting bases matrix A was assumed to have signatures specific to each class. Hence the bases matrix was used as the input for the spectral clustering algorithms which was formulated in-house [12]. The results obtained by this are shown in Fig.3.

The cluster signatures of each class after applying spectral clustering can be observed in Fig. 3. It can be observed that while the cluster signatures of artefacts are isolated from other cluster signatures, the cluster signatures of fetal movements and mothers' respiratory movements are overlapping each other. This is not a favorable result. Therefore, it was decided to include a preprocessing step to eliminate mothers' respiratory movement realizations. For this further analysis of mothers' respiratory movement signals were conducted.

When further analysis on mothers' respiratory realizations were made, it was observed that it has a close resemblance to White Gaussian noise. One of the simplest analysis methods to identify White Gaussian noise is to compare the value of the Standardized Fourth Central Moment, which is also referred to as the kurtosis. Hence a simple kurtosis calculation was carried out on all realizations and the results obtained are shown in Fig.4.

As it can be seen in the Fig.4 the kurtosis values of mothers' respiratory movement realizations are vacillating around 3 where kurtosis value of fetal movements and other artefacts have different values. Therefore, a simple kurtosis calculation was conducted as a preprocessing step where a threshold was set to remove mothers' respiratory movement realizations. Then the remaining realizations which contain predominant variations were analyzed following the same procedure mentioned above. And the resulting cluster distribution is shown in Fig.5.

It can be observed in Fig.5 that the previous overlapping is not present. Hence fetal movement realizations and other artefacts can be classified with higher accuracy.

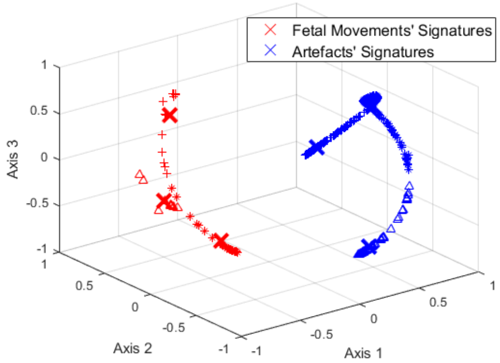

Fig. 5. Example of a presentation of data in a pie chart

Finally, remaining realizations were used to test the algorithm. When testing the Euclidean distance from a signature point to the test signal point is measured and grouped into a relevant group with minimum distance.

IV. RESULTS AND DISCUSSION

Two algorithms were implemented on the data set to classify fetal movements. Initially, a two-step method was implemented where a Non-negative Matrix Factorizations was conducted and the resulting Bases matrix was fed into a spectral clustering algorithm. But as seen in Fig. 3 there is an overlap between mothers' respiratory movement realizations and fetal movement realizations. This can result in increasing the false positives. In our application, an increase in false positives pose a huge threat to fetal health. When a false positive occurs the algorithm will identify that a fetal movement has occurred where in reality no fetal movement has occurred. This can lead to the mother to believe that the fetus is moving where it is not. This in turn will result in the inability to consult an obstetrician promptly. However, true negatives can lead to superfluous consultations, which are undesirable but do not cause much harm to the fetus.

As a solution for the issues a three-step method including a preprocessing step to remove mothers respiratory movement realizations was implemented. The resulting confusion matrix can be observed in Table 1. As it can be observed in the confusion matrix the preprocessing step was able to identify 89.41% of mothers' respiratory movement realizations and the remaining algorithm was able to identify 96.55% fetal movements accurately. Also, the algorithm has identified 9.41% of mothers' respiratory movements and 11.11% of other artefacts as fetal movements.

V. CONCLUSION

Table 1. Confusion matrix for the three-step method

	True Category		
	Fetal Movement	**Respiratory Movements**	**Other Artefacts**
Fetal Movement	96.55%	9.41%	11.11%
Respiratory Movements	0.00%	89.41%	0.00%
Other Artefacts	3.45%	1.18%	88.89%

In this research two methods to analyze accelerometric fetal movement data detection were compared. It was observed that while the two-step method performed poorly by adding a simple preprocessing step the accuracy of the algorithm was improved comparatively. Therefore, it can be concluded that fetal movement can be identified by applying the above mentioned three-step algorithm to accelerometric data. However, further studies are required to analyze the behavior of fetal movement in larger populations.

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