Automatic Monodimensional EHG Contractions' Segmentation

Amer Zaylaa[1], Ahmad Diab[2], Mohamad Khalil[3], and Catherine Marque[1]
[1]BioMécanique et BioIngénierie, Université de Technologie de Compiègne, France
[2]Faculty of Public Health, Lebanese University, Lebanon
[3]Faculty of Engineering, Lebanese University, Lebanon

Abstract: *Until recently, many studies have been achieved for the sake of automatically segmentation of the Electrohysterogram (EHG) in order to identify the efficient uterine contractions but the most of them encountered the presence of other events such as motion artifacts and other kind of contractions despite of the use of efficient filtering methods. In this study, we apply an online method which is developed previously and known by Dynamic Cumulative Sum (DCS) on monopolar EHG signals acquired through a 4x4 electrodes matrix with and without Canonical Correlation Analysis and Empirical Mode Decomposition (CCA-EMD) denoising method, then on monopolar EHG after wavelet decomposition. The detected segments are driven through an automatic concatenation technique of detected event time from all channels in order to reduce the unwanted segments, the obtained segments then undergo to implemented Margin validation test in order to classify among them. Sensitivity of detected contractions and other detected events rate referring to identified contractions by expert have been calculated in order to track the efficiency of the fully automated multichannel segmentation method. Additional EHG filtering techniques like CCA-EMD method seems to be better but effective time cost. Further studies should be achieved in order to decreasing the other events rate for the sake of fully identifying the uterine contractions.*

Keywords: *EHG signal, dynamic cumulative sum, CCA-EMD denoising method, automatic segmentation, wavelet decomposition, margin validation test.*

Received October 14 2018; accepted January 23 2019

1. Introduction

Humanity encounters a continuous rising in preterm birth (before 37 completed weeks of gestation) beyond World Health Organization (WHO). Indeed, an estimated of 15 million babies are born preterm each year, which indicates that there is more than 1 in 10 new born babies. Preterm birth is responsible for approximately 1 million deaths in 2015 [12] where its complications are the leading cause of death among children under 5 years of age.

The uterine electrical activity recorded from the abdominal surface is called Electrohysterogram (EHG) and presents rapid non-stationarity or transitions which leads to primary problem of EHG segmentation.

Multichannel EHG signals recording is usually obtained by using multiple electrodes placed on the pregnant woman's abdomen and is considered as a proper mean to study the propagation of the electrical activity in the uterine muscle of a pregnant woman [9].

Since a high spatial resolution is needed in order to obtain a precise mapping and features of uterine EHG contractions of this complex organ the uterus, multichannel signals processing becomes highly recommended in most of EHGs applications [1, 7]. The total number of electrodes is however limited by the abdominal surface, especially when the electrodes should be positioned along or as near as possible to the median vertical axis, in order to get the better Signal-Noise Ratio (SNR) [7].

For the recent past, pregnancy and labor uterine contractions are usually monitored by using a system called to codynamometer. However, this system is not a reliable technique since the obtained measurements are not fully precise and depend to a large extent on the subjective criteria of the operator [13].

In order to segment events, many algorithms and methods were addressed to track the transitions in non-stationary signals such as Algorithm of Neyman–Pearson [8], Brandt algorithm [5], Innovation Whiteness [2], Hinkley Divergence Test [3],Cumulative Sum method (CuSum) [4], Dynamic Cumulative Sum method (DCS) [11,15], nonlinear correlation coefficient (H2) [14].

The Canonical Correlation Analysis and Empirical Mode Decomposition (CCA-EMD) denoising method consists of the use of a combination of Blind Source Separation method using Canonical Correlation Analysis (BSS-CCA) and Empirical Mode Decomposition (EMD) methods to denoise multi-channel monopolar EHG recordings. It has been proven by simulation that CCA-EMD method successfully removed noise with muscle activity conservation even in presence of a low Signal to Noise ratio (SNR) (2 dB) [9].

The aim of this study is to detect automatically all events by using the DCS method applied on monopolar EHG signals with and without CCA-EMD denoising method. We then automatically concatenate the detected segments from all 16 channels in order to improve the results of a previous study where the concatenation of the detected segments has been performed manually [15]. Finally, we validate the obtained results, by using the Margin validation test, and then compute the sensitivity of the detection of contractions and other events by referring to contractions identified by expert.

2. Materials and Methods

2.1. Data

In our study, EHG signals have been collected from 36 pregnant women by placing an array of16electrodesarranged in a 4×4 matrix positioned on the woman's abdomen and two reference electrodes on each hip (Figure 1) by using a standardized protocol [10]. The 16 monopolar EHG signals are digitized with a 200 Hz sampling frequency. In addition, a tocodynamometer is placed on the abdomen of the pregnant woman (Figure 1), in order to assist the expert to identify the contractions.

The 16 monopolar EHG signals, acquired from the 4x4 electrode matrix, undergo a fourth-order [0.3-5 Hz]Butterworth filter that removes frequencies below 0.3 Hz which can be seriously affected by movement artifacts related, for example, to respiration or fetal and maternal movements. Then, the obtained monopolar signals are denoised by CCA-EMD method [9] in order to compare the results between those filtered and not filtered when applying the DCS method.

2.2. Method

The DCS method is considered as a powerful method for detecting changes or transitions in signals when someone wants to follow local changes in the signals and the characteristics of the changes are unknown. Indeed, a change in a signal may affect variance, frequency distribution or both at the same time.

This detection approach, called the DCS, can be considered as a repeated sequence around the point of change k. It is based on the local cumulative sum of the likelihood ratios between two local hypotheses estimated around the current instant j. These two dynamic hypotheses H_a^j and H_b^j (a: after, b: before) are estimated using two windows of length N, before and after the instant j respectively as follows:

- H_b^j : x_i ; i = {j-N+1,..., j} follows a density probability distribution $f_{\theta_b}(x_i)$.
- H_a^j : x_i ; i = {j+1,..., j+N} follows a density probability distribution $f_{\theta_a}(x_i)$.

The parameters of the hypothesis H_b^j and $\hat{\theta}_b{}^j$ are estimated from N points before the instant j and from N points after the instant j for the hypothesis H_a^j and $\hat{\theta}_a{}^j$.

At time j, we define DCS as the sum of the logarithms of the likelihood ratios from the beginning of the new segment of the signal to the instant j:

$$DCS\,(H_a^j, H_b^j) = \sum_{i=1}^{j} ln \frac{f_{\hat{\theta}_a{}^i}(x_i)}{f_{\hat{\theta}_b{}^i}(x_i)} = \sum_{i=1}^{j} \hat{s}_i \qquad (1)$$

Figure 1. Position of 4x4 matrix electrodes with tochodynamometer.

Where $\hat{s}_i$ is the logarithm of the likelihood ratio to a local character. The parameters of the two hypotheses are re-estimated at each step in the two windows of N points around the current point j.

It has been demonstrated in [11] that the DCS function reaches its maximum at the time of change k.

The detection function used to estimate the instant of change is expressed by:

$$g_j = \max_{1 \le i \le j} [\, DCS\,(H_a^j, H_b^j)\text{-}\, DCS\,(H_a^j, H_b^j)] \qquad (2)$$

The stop time is: t_s= INF {j:g_j ≥h};

Where h is being a fixed threshold.

By applying the DCS method, a series of detected instants were obtained. All detected instants from all 16 monopolar EHG signals with and without CCA-EMD denoising method were first projected temporarily then were subject to an automatic concatenation phase by averaging two consecutives instants when their difference is less than a predefined threshold value chosen as a third of the average of all 395 contractions duration identified by the expert from all records. The obtained concatenated instants reflect subsequently the start and the end of each segment.

2.3. Wavelet Transform and Scaling Choice

The wavelet transform makes it possible to efficiently analyze signals in which phenomena of very different scales are combined. The translation and expansion parameters are the two arguments of the wavelet transform. The continuous wavelet transform of a signal $x(t)$ takes the form:

$$T_x^{\varphi}(a,b) = \int x(t)\varphi_{ab}(t)dt \quad (3)$$

Each signal can be decomposed into details and approximations, and the shape of the scale function is defined by:

$$\emptyset_{mn}(t) = 2^{m/2}\emptyset(2^m t - n) \quad (4)$$

Where m indicates the scales, n indicates the translation in time.

The choice of wavelet and scaling is very important that is why symlet 5 is chosen and details 1 to 5 have been selected in our study based on the efficiency of this choice in [6].

2.4. Validation Test, Sensitivity and Other Events Rate

2.4.1. Margin Validation Test

With the concatenated segments or detected events are ready to be assessed. We use a Margin validation test. to classify the detected events as either totally detected or partially detected contractions or other events.

The Margin validation test is based on the creation of two symmetric margins at the beginning and the end of each contraction identified by the expert (Figure 2). This margin is computed as the maximum between 10 seconds and the third of the length of each identified contraction. Then we test if the beginning and end times of each detected event fit within the defined margins. We thus obtain t classes of events: totally validated, partially validated, and not validated contractions.

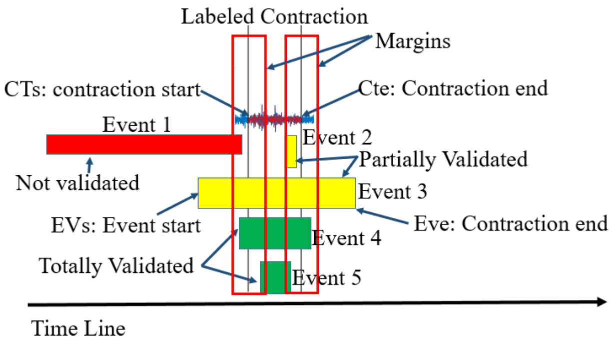

Figure 2. Validation events using Margin validation test.

2.4.2. Sensitivity and Other Events Rate

For each record, the sensitivity of DCS method reflects the ratio of the sum of partially and totally detected contractions over all detected events or segments, while the other events rate reflects the ratio of other detected events which is not considered as contractions over all detected events.

3. Results

After choosing the parameters of the DCS method (size of the sliding window 'N', threshold of the detection function 'h'), we obtain the detected instants, indicated by a black line in Figure 3. Thus, each pair of consecutive instants reflects the starting and ending point of a detected event.

Numbers of labeled contractions identified by the expert on each recording are in blue color. We can also notice in this figure the numbers of totally detected contraction (black color), partially detected contraction (yellow color) or other detected event (green color) obtained after application of the Margin validation test.

When counting the global (partially+totally) detected contractions of each record as shown in table 1, we get an average of DCS method sensitivity of 91.18% for monopolar EHG signals without CCA-EMD denoising method with an average of other detected events of 50.3% (counted as: the number of other detected events over the sum of other detected events and the global number of validated contractions) where we got 534 other events. In addition, we obtain 94.01 % as the average of DCS method sensitivity for monopolar EHG signals with CCA-EMD denoised method comparing to an average of 55.25 % for the other detected event where 585 other events were detected.

By applying the dynamic cumulative on the monopolar EHG signals after symlet 5 transform and especially on the details 1 to 5 signals for all 16 channels, we obtain different records' sensitivity ranging from 60 to 100% with an average of 83.3 % while other records' other events rate is ranging from 0 to 96 % with an average of 62.8%, where 730 other events were detected.

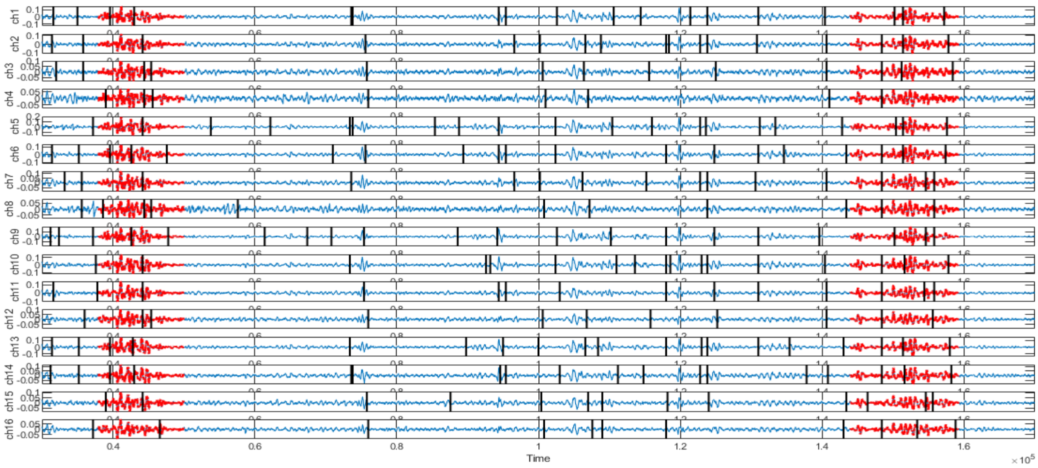

Figure 3. Detected instants by DCS for each monopolar EHG.

Table 1. Evaluation of sensitivity and other events rate of 36 EHG records with, without denoising CCA-EMD and with symlet 5 transform.

Monopolar EHG	without CCA_EMD		with CCA_EMD		with symlet 5 transform	
Record	**Sensitivity %**	**Other Events %**	**Sensitivity %**	**Other Events %**	**Sensitivity %**	**Other events %**
Record 1	100.0	42.1	87.5	33.3	87.5	58.8
Record 2	100.0	75.8	100.0	57.1	60.0	70.0
Record 3	100.0	60.0	93.3	61.5	93.3	62.2
Record 4	100.0	50.0	100.0	68.3	87.5	74.1
Record 5	100.0	38.5	100.0	52.3	68.8	35.3
Record 6	87.5	46.7	100.0	66.7	87.5	12.5
Record 7	100.0	68.4	100.0	58.8	83.3	79.2
Record 8	100.0	59.4	100.0	64.0	71.4	16.7
Record 9	100.0	50.0	100.0	57.1	100.0	54.5
Record 10	100.0	71.9	100.0	68.2	100.0	83.5
Record 11	100.0	74.3	100.0	69.2	100.0	87.2
Record 12	100.0	52.6	100.0	53.8	100.0	80.8
Record 13	100.0	50.0	100.0	20.0	100.0	76.5
Record 14	100.0	40.9	87.5	38.5	100.0	65.2
Record 15	100.0	40.6	94.4	48.6	66.7	50.0
Record 16	95.7	8.7	91.5	12.0	70.2	29.8
Record 17	100.0	64.3	100.0	70.8	100.0	78.9
Record 18	100.0	45.2	100.0	51.4	100.0	75.0
Record 19	100.0	75.0	100.0	74.4	100.0	86.4
Record 20	100.0	70.6	100.0	62.1	77.8	74.1
Record 21	100.0	65.0	100.0	78.3	100.0	96.0
Record 22	72.7	53.8	72.7	75.0	63.6	75.9
Record 23	92.3	67.4	76.9	69.7	76.9	76.2
Record 24	95.7	36.1	95.7	47.6	87.0	41.2
Record 25	76.0	16.7	92.0	32.4	68.0	34.6
Record 26	100.0	72.7	100.0	87.0	50.0	91.7
Record 27	100.0	42.9	100.0	20.0	75.0	57.1
Record 28	75.0	87.2	75.0	86.0	100.0	52.9
Record 29	50.0	65.0	80.0	50.0	60.0	66.7
Record 30	83.3	0.0	94.4	34.4	77.8	0.0
Record 31	91.7	20.0	100.0	43.3	100.0	76.0
Record 32	68.8	0.0	93.8	36.7	62.5	33.3
Record 33	88.9	0.0	94.4	11.5	88.9	65.2
Record 34	100.0	85.0	100.0	82.4	100.0	94.3
Record 35	25.0	66.7	75.0	71.4	75.0	72.7
Record 36	80.0	50.0	80.0	75.0	60.0	72.7
Average	91.18	50.31	94.01	55.25	83.3	62.8

4. Discussion

In this paper, we have presented a comparison between the results obtained by applying the dynamic cumulative sum on monopolar EHGs signals with and without denoising by CCA-EMD method and on details signals of monopolar EHG signals in a monodimensional study.

Monopolar EHG signals denoised by CCA-EMD method's results present not only an increase in sensitivity of DCS method, which reached 94.01% of sensitivity, but also an increase in the totally detected contractions number that reached 97 contractions from all recordings with denoising compared to 52 contractions on not denoised monopolar EHG signals and 36 contractions totally detected when applying wavelet decomposition. Despite advantages by using CCA-EMD denoising method when applying the DCS method, there is real time inconvenient due to the increase of other detected events from 50.3% for not denoised EHG toget 55.25% for denoised ones and 62.8% by applying DCS on details signals. Furthermore, denoising induces an average 3.4-fold increase in the execution time when applying CCA-EMD which is an effective time cost.

The repartition of the detected events obtained after applying the DCS method on monopolar EHG signals denoised with CCA-EMD is presented in Figure 4. As shown, the totally detected contractions number is very low comparing to partially detected contractions
number; and this issue could be turned to the event's tracking technique that considers the first instant of change as the beginning of new event while the consecutive one is considered as the end of this event.

In addition, the number of other detected events reaches the maximum level when applying the DCS on details signals after symlet 5 transform of monopolar EHG, and this could be explained by higher events with different frequency information's' distribution when applying wavelet decomposition.

By comparing results with a recent work in [14] based on nonlinear correlation coefficient (H2) method, they obtain an excellent detection rate (96%) and other events rate (92%). To be noted, that EHGs signals database don't follow the same conditions (where 51 records were used in [14]) with different computation method of other events rate (where in [14], the other events rate was computed by dividing the other detected events over the contractions identified by expert).

5. Conclusions

To conclude, by using an automatic concatenation of the results from different channels obtained by applying the dynamic cumulative sum, we obtain an automatic segmentation of contractions on the EHG signals. But the high number of other detected events remain an issue that should be solved for clinical use.

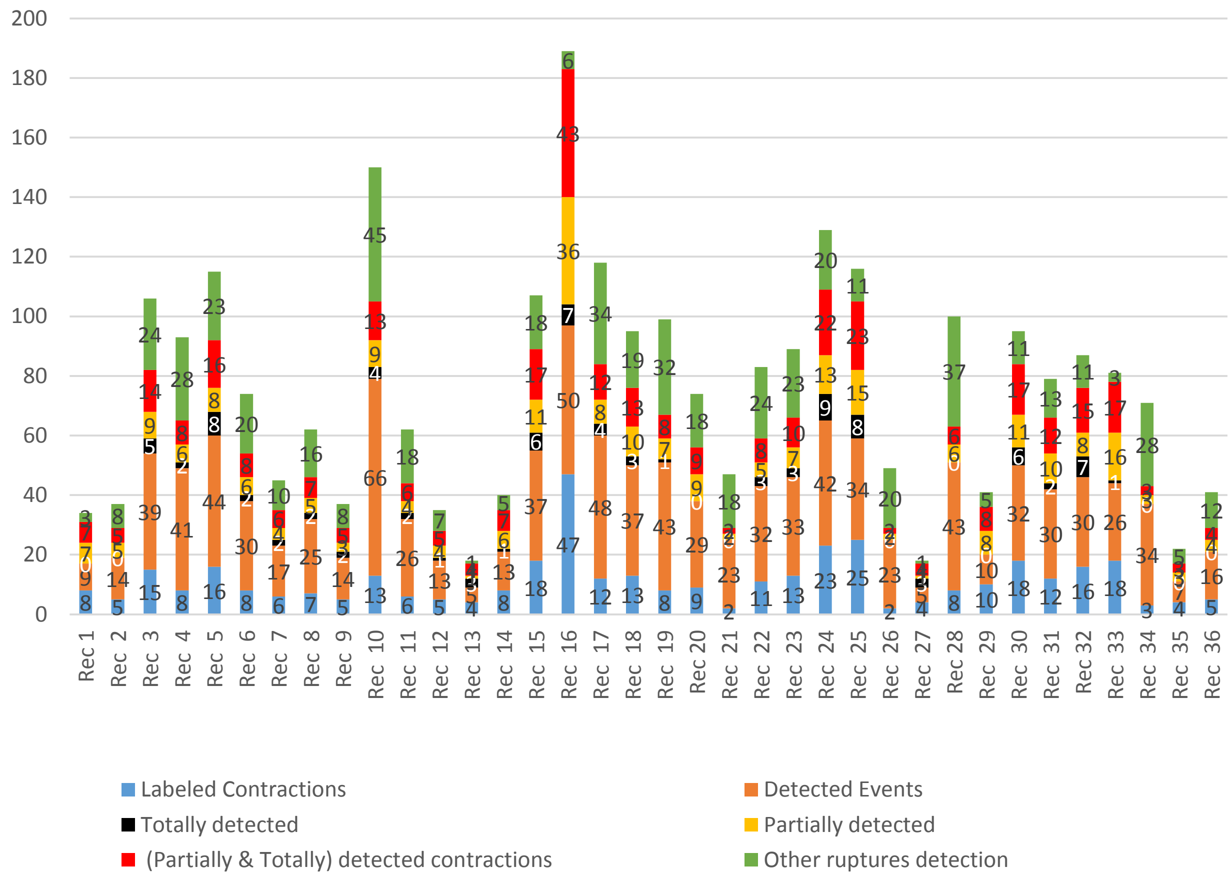

Figure 4. DCS method Assessment for all 36 recordings proceeded by CCA-EMD denoising method.

6. Perspectives

We are looking forward to enhance the events' tracking method and to apply the dynamic cumulative sum on bipolar EHG signals in monodimensional and multidimensional study in order to try to increase the sensitivity of the DCS method and reduce the other detected events rate in the same time.

Acknowledgement

This research has been supported by University of Technology of Compiegne, CEDRE and Al Koura Hospital.

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Catherine Marque is presently Professor at Compiègne University, Compiègne, France, in the UMR 7338 Biomechanics and Bioengineering (BMBI) lab. After a graduation in mechanical engineering from ENSAM (Paris, France), and a Master degree in Biomedical Engineering from the EcolePolytechnique de Montréal (Canada), she received the Ph.D. degree and the "Habilitation à diriger des recherches" (HDR) from Compiègne University. Her research focuses on biomedical signal processing and modeling. She is interested in the study of uterine contractility, by processing the uterine electrical activity recorded on the mother's abdomen (electrohysterogram, EHG) in order to detect preterm labor. Since she integrated the BMBI research lab, she has been developing an international team that works on processing and modeling the EHG. Her aim is to understand the links existing between EHG characteristics and the physiological phenomena controlling uterine contraction efficiency (cell excitability, uterine synchronization) for clinical diagnosis purpose. She has recently developed a multi-scale electrical (cell, tissue, organ, abdomen) and multi-physics (electrical, mechanical) model that permits to link EHG characteristics to the uterine muscle behavior (channel dynamics, electrical diffusion, sensitivity to stretching, mechano-transduction), as well as specific processing tools to investigate the EHG connectivity. These recent results permit to evidence that the uterine synchronization is the consequence not only from a simple electrical diffusion process, but also from an electromechanical coupling related to tissue stretching, a new hypothesis recently presented by physiologists. She has been coordinator of many national and international research projects that permitted her to develop various collaborations and to supervise 22 PhD and about 30 Masters thesis. She has taken the responsibility for administrative tasks, related either to teaching (engineer, Master, Doctoral education) or to research management (research unit, Regional research group…).

Mohamad Khalil is currently professor, teacher and researcher at Lebanese University, faculty of engineering. He received the DEA in biomedical engineering from the University of Technology of Compiegne (UTC) in France in 1996. He received his Ph.D from the University of Technology of Troyes in France in 1999. He received his HDR (Habilitation adiriger des recherches) from UTC in 2006... He is the chair of the EMBS chapter in Lebanon, chair of ICABME international Conference. His current interests are the signal and image processing problems: detection, classification, analysis, representation and modeling of non stationary signals, with application to biomedical signals and images.

Ahmad Diab received the degree in Biomedical Engineering from the Islamic University of Lebanon, Khaldeh, Lebanon, in 2010.
And the M.Sc. degree in Medical and Industrial Processing and System from the Lebanese University, Tripoli, Lebanon, in 2011.
Also he received his Ph.D. degree from the University of Technology of Compiègne, Compiègne, France and Reykjavik University, Reykjavik, Iceland in 2014.
He was a Research Engineer at Azm center for research in biotechnology and its application, Lebanese University between 2014 and 2017.
He is currently an Assistant Professor at the Lebanese University and many private universities.
His current research interests include signal processing problems: characterization, classification, nonlinear analysis, source localization, with application to biomedical signals.

Amer Zaylaa received the degree in Biomedical Engineering from the Islamic University of Lebanon, Khaldeh, Lebanon, in 2008, the Master of research degree in Medical and Industrial Processing and System from the Lebanese University, Tripoli, Lebanon, in 2015.
He is currently a PhD candidate in final year at University of Technology of Compiègne, section: Biomechanics and Bioengineering.
He is currently the chair of biomedical engineering department at koura hospital since January 2009.