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EHG Signal Classification for Term and Pre-Term Pregnancy Analysis

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ABSTRACT

Early prediction of premature pregnancy reduces neonatal death and helps in adoption of treatment well suited for the pre-term pregnancy state. There are scads of work done in the area of term and pre-term pregnancy analysis like artificial intelligence, regressive models, and higher order statistical models. This paper proposes a four-level decomposition of Electrohysterography (EHG) signals using Discrete Wavelet Transform (DWT) based on pyramid algorithm to obtain the final feature vector matrix. Classification is done using Support Vector Machines (SVM) by dividing the data into test and training sets. It is validated on a well-known benchmark database from Physionet Database. The proposed method can be used for real time implementation owing to low computational cost, high speed and its feasibility to be implemented on hardware. The encouraging experimental results show that the technique gives an accuracy of 97.8% and can be a promising tool for investigating the risk of preterm labor.

Keywords : Discrete wavelet transform, labor time detection, term and pre-term pregnancy, Support Vector Machines, EHG

I. INTRODUCTION

Preterm birth, also known as premature birth or delivery, is described by the World Health Organisation (WHO) as the delivery of babies who are born, alive, before 37 weeks of gestation [1]. In contrast, term births are the live delivery of babies after 37 weeks, and before 42 weeks. According to the WHO, worldwide in 2010, preterm deliveries accounted for 1 in 10 births [1]. In 2009, in England and Wales, 7% of live births were also preterm (http://ons.gov.uk). Preterm birth has a significant adverse effect on the new born, including an increased risk of death and health defects. The severity of these effects increases the more premature the delivery is. Approximately, 50% of all perinatal deaths are caused by preterm delivery [2], with those surviving often suffering from afflictions, caused by the birth. These include impairments to hearing, vision, the lungs, the cardiovascular system and non-communicable diseases; up to, 40% of survivors of extreme preterm delivery can also develop chronic lung disease [3]. In other cases, survivors suffer with neuro-developmental or behavioural defects, including cerebral palsy, motor, learning and cognitive impairments. In addition, preterm births also have a detrimental effect on families, the economy, and society. In 2009, the overall cost to the public sector, in England and Wales, was estimated to be nearly £2.95 billion [4]. However, developing a better understanding of preterm deliveries can help to create preventative strategies and thus positively mitigate, or even eradicate, the effects that preterm deliveries have on babies, families, and society and healthcare services.

Preterm births can occur for three different reasons. According to [2], roughly one-third are medically indicated or induced; delivery is brought forward for the best interest of the mother or baby. Another third occurs because the membranes rupture, prior to labour, called Preterm Premature Rupture of Membranes (PPROM). Lastly, spontaneous contractions (termed preterm labour or PTL) can develop. However, there is still a great deal of uncertainty about the level of risk each factor presents, and whether they are causes or effects. Nevertheless, in [2] some of the causes of preterm labour, which may or may not end in preterm birth, have been discussed. These include infection, over-distension, burst blood vessels, surgical procedures, illnesses and congenital defects of the mother's uterus and cervical weakness. Further studies have also found other risk factors for PTL/PPROM [5,6]. These include a previous preterm delivery (20%); last two births have been preterm (40%), and multiple births (twin pregnancy carries a 50% risk). Other health and lifestyle factors also include cervical and uterine abnormalities, recurrent antepartum haem- orrhage, illnesses and infections, any invasive procedure or surgery, underweight or obese mothers, ethnicity, and social deprivation, long working hours/late nights, alcohol and drug use, and folic acid deficiency.

As well as investigating preterm deliveries, several studies have also explored preterm labour (the stage that directly precedes the delivery). However, in spite of these studies, there is no internationally agreed definition of preterm labour. Nonetheless, in practice, women who experience regular contractions, increased vaginal discharge, pelvic pressure and lower backache tend to show threatening preterm labour (TPL). While this is a good measure, Mangham et al., suggest that clinical methods for diagnosing preterm labour are insufficient [4]. Following a medical diagnosis of TPL, only 50% of all women with TPL actually deliver, within seven days [2]. In support of this, McPheeters et al., carried out a similar study that showed 144 out of 234 (61.5%) women diagnosed with preterm labour went on to deliver at term [7]. This can potentially add significant costs, and unnecessary interventions, to prenatal care. In contrast, false-negative results mean that patients requiring admittance are turned away, but actually go on to deliver prematurely [8].

Predicting preterm birth and diagnosing preterm labour clearly have important consequences, for both health and the economy. However, most efforts have concentrated on mitigating the effects of preterm birth. Nevertheless, since this approach remains costly [1], it has been suggested that prevention could yield better results [9]. Effective prediction of preterm births could contribute to improving prevention, through appropriate medical and lifestyle interventions. One promising method is the use of Electrohyster- ography (EHG). EHG measures electrical activity in the uterus, and is a specific form of electromyography (EMG), the measurement of such activity in muscular tissue. Several studies have shown that the EHG record may vary from woman to woman, depending on whether she is in true labour or false labour and whether she will deliver term or preterm. EHG provides a strong basis for objective predication and diagnosis of preterm birth.

Many research studies have used EHG for prediction or detection of true labour. In contrast, this paper focuses on using EHG classification to determine whether delivery will be preterm or term. This is achieved by comparing various machine-learning classifiers against an open dataset, containing 300 records (38 preterm and 262 term) [10], using a signal filter and pre-selected features, which are suited to classifying term and preterm records. The results indicate that the selected classifiers outperform a number of approaches, used in many other studies.

In analysis of pregnancy for labor period detection the use of non – invasive techniques is highly encouraged. One such promising technique is the uterine Electrohysterography (EHG) signals. The EHG records correspond to the activity of the uterine muscles. The main events extracted from the uterine EHG are the contractions (CT). The electrical activity during pre-term labor (labor prior to 37 weeks of completed gestation) is significantly different from the activity of term labor. These differences prove to be helpful in identifying the nature (term or preterm) of the delivery. Owing to its simple and non- invasive nature this technique finds huge acceptance in hospitals. The premature delivery can be a threat to the child if not detected timely, as it may lead to birth of handicapped child with mental, neurological or behavioral abnormalities. But, among 80% cases it causes neonatal death. Thus, knowing the time of labor can help in adoption of treatment well suited for the preterm pregnancy state.

Due to the complications involved it is an extremely difficult task to predict the labor time hence, it is necessary to rely only on a technique having very high accuracy of separating the term pregnancy from the pre-term pregnancy.

Review of Literature

A review of previous literature shows that immense work has been done in noninvasive techniques for determination of preterm delivery. Several model-based approaches [1], [5], [6], [7], [12], [13] have been proposed in this area. Jerzy et. al [1] classified the term and pre-term data using the Lagrangian Support Vector Machines (SVM). In [5] Marwa Chendeb et. al used wavelet transform and then classified using artificial neural networks and SVM. Various linear and non-linear processing techniques were used by G. Fele et. al [6]. In [12] classical techniques of data analysis, such as Principal Component Analysis (PCA) and Discriminant Analysis (DA) have been used. In [7], [13] Artificial Neural Networks (ANN) has been used on the EHG signals quantified by finding the means and standard deviations of the power spectrum. But, still this area lacks an effective practical method to access whether the uterine signals have entered the phase of uterus activity-burst that may indicate labor time.

Electrohysterography

Electrohysterography (EHG) is the term given for the recording of electrical activity of the uterus, in the time domain. In order to retrieve EHG signals, bipolar electrodes are adhered to the abdominal surface. These are spaced at a horizontal, or vertical, distance of 2.5 cm to 7 cm apart. Most studies, including [10], use four electrodes, although one study utilizes two [11]. In a series of other studies, sixteen electrodes were used [12–17], and a high- density grid of 64 small electrodes were used in [18]. The results show that EHG may vary from woman to woman. This is dependent on whether she is in true or false labour, and whether she will deliver at term, or prematurely.

A raw EHG signal results from the propagation of electrical activity, between cells in the myometrium (the muscular wall of the uterus). This signal measures the potential difference between the electrodes, in a time domain. The electrical signals are not propagated by nerve endings; however, the propagation mecha- nism is not clear [19]. Since the late 70s, one theory suggests that gap junctions are the mechanisms responsible. Nevertheless, more recently it has been suggested that interstitial cells, or stretch receptors may be the cause of propagation [20]. Gap junctions are groups of proteins that provide channels of low electrical resistance between cells. In most pregnancies, the connections between gap junctions are sparse, although gradually increasing, until the last few days before labour. A specific pacemaker site has not been conclusively identified, although, due to obvious physiological reasons, there may be a generalised propagation direction, from the top to the bottom of the uterus [21].

The electrical signals, in the uterus, are 'commands' to contract. During labour, the position of the bursts, in an EHG signal, corresponds roughly with the bursts shown in a tocodynamometer or intrauterine pressure catheter (IUPC). Clinical practises use these devices to measure contractions. More surprisingly, distinct contraction-related, electrical uterine activity is present early on in pregnancy, even when a woman is not in true labour. Gondry et al. identified spontaneous contractions from EHG records as early as 19 weeks of gestation [22]. The level of activity is said to increase, as the time to deliver nears, but shoots up especially so, in the last three to four days, before delivery [23]. As the gestational period increases, the gradual increase in electrical activity is a manifes- tation of the body's preparation for the final act of labour and parturition. In preparation for full contractions, which are needed to create the force and synchronicity required for a sustained period of true labour, the body gradually increases the number of electrical connections (gap junctions), between cells. In turn, this produces contractions in training.

Before analysis or classification occurs, EHG signals, in their raw form, need pre-processing. Pre-processing can include filtering, de- noising, wavelet shrinkage or transformation and automatic detection of bursts. Recently, studies have typically focused on filtering the EHG signals to allow a bandpass between 0.05 Hz and 16 Hz [24–28]. However, there are some that have filtered EHG recordings as high as 50 Hz [19]. Nevertheless, using EHG with such a wide range of frequencies is not the recommended method, since more interference affects the signal.

Feature Extraction from Elecrohysterography

The collection of raw EHG signals is always temporal. However, for analysis and feature extraction purposes, translation, into other domains, is possible and often required. These include frequency representation, via Fourier Transform, [15], [28–30] and wavelet transform [24,27], [30–33]. The advantage of frequency-related parameters is that they are less susceptible to signal quality variations, due to electrode placement or the physical character- istics of the subjects [26]. In order to calculate these parameters, a transform from the time domain is required, i.e., using a Fourier transform of the signal. In several of the studies reviewed, in order to obtain frequency parameters, Power Spectral Density (PSD)is used. Peak frequency is one of the features provided within the Term- Preterm ElectroHysteroGram (TPEHG) dataset, used within this paper. It describes the frequency of the highest peak in the PSD. Most studies focus on the peak frequency of the burst, in both human and animal studies, and is said to be one of the most useful parameters for predicting true labour [34]. On the other hand, the study by [10] found medium frequency to be more helpful in determining whether delivery was going to be term or preterm.

Several studies have shown that peak frequency increases, as the time to delivery decreases; generally, this occurs within 1–7 days of delivery [11,19,24,26,30,35]. In particular, the results in [28] show that there are, statistically, significant differences in the mean values of peak frequency and the standard deviations in EHG recordings taken during term labour (TL) and term non-labour (TN) and also between preterm labour (PTL) and preterm non-labour (PTN).

In comparison to peak frequency, the TPEHG study [10] found that median frequency displayed a more significant difference, between term and preterm records. When considering all 300 records, the statistical significance was p = 0.012 and p = 0.013, for Channel 3, on the 0.3–3 Hz and 0.3–4 Hz filter, respectively. Furthermore, this significance (p = 0.03) was also apparent when only considering early records (before 26 weeks of gestation), with the same 0.3–3 Hz filter, on Channel 3. The TPEHG study [10] concluded that this might have been due to the enlargement of the uterus, during pregnancy, which would affect the position of electrodes. The placement of the Channel 3 electrode was, approximately, always 3.5cm below the navel. However, as pregnancy progressed, this would mean that the electrode would move further away from the bottom of the uterus (cervico-isthmic section). If a generalised pacemaker area actually exists, and it is at the cervico-isthmic section, then, as pregnancy progresses, its position would move further and further away from the electrode, resulting in a diminished record of the signal. Whether this explanation is true or not, the results of [10] show that, the discriminating capability of median frequency is somehow diminished, after the 26th week.

Amplitude-related EMG parameters represent the uterine EMG signal power, or signal energy. However, a major limitation is that the differences in patients can easily affect these parameters. Patients may differ in the amount of fatty tissue they have, and the conductivity of the skin–electrode interface, which leads to differences in the attenuation of uterine signals [8,26,34]. Examples of amplitude-related parameters include root mean square, peak amplitude and median amplitude.

Using the Student's t-test, [10] found that root mean square might be useful in distinguishing between whether the information was recorded early (before 26 weeks of gestation) or late (after 26 weeks). The results obtained are in agreement with [19,30] and [36], who found that the amplitude of the power spectrum increased, just prior to delivery. This was despite only analysing the root mean square values, per burst, rather than the whole signal. On the other hand, other studies did not find that amplitude- related parameters displayed a significant relationship to gesta- tional age or indicate a transition to delivery (within seven days) [23,25,28]. Some of these discrepancies may be due to the differences between the characteristics in the studies: [10] compared records before and after 26 weeks, whereas [25] only examined records after the 25th week; [29] and [35] studied rat pregnancy, in contrast to human pregnancy. The frequency band used in [30] and [19] was also a much broader band than in other studies (0.3–50 Hz; no bandwidth given for [36]), and the studies by [29] and [35] measured per burst, whilst [25] measured the whole signal.

Meanwhile, the TPEHG study [10] could not find any significant difference in root mean squares between preterm and term records. However, [25] did find that the root mean squares,in preterm contractions, were higher (17.5 mv 67.78), compared to term contractions (12.2 mV 66.25; p,0.05). The results, from [25], could not find a correlation between root mean squares and the weeks left to delivery. Nevertheless, they do suggest that a greater root mean square value was, for the most part, a static symptom that indicated a woman's dispensation to give birth prematurely. They also found that the root mean square values, within each pregnancy, did increase within a few days of birth.

Overall, the results suggest that there is no significant difference in the amplitude-related parameters between term and preterm deliveries, when taken during labour, or close to it. However, there may be considerable differences earlier on in the pregnancy. This suggests that by the time of delivery, any differences have equalised themselves.

Sample entropy measures the irregularity of a time series, of finite lengths. This method was introduced by [37] to measure complexity in cardiovascular and biological signals. The more unpredictable the time series is, within a signal recording, the higher its sample entropy. The process is based on calculating the number of matches of a sequence, which lasts for m points, within a given margin r. The disadvantage of this technique is the requirement to select two parameters, m and r. However, sample entropy did show a statistical difference between term and preterm delivery information, recorded either before or after the 26th week of gestation, when using any of the filters, but only using the signal from Channel 3 [10].

Term and Preterm Classification

Computer algorithms, and visualization techniques, are funda- mental in supporting the analysis of datasets. More recently, the medical domain has been using such techniques, extensively.

Artificial Neural Networks (ANN) have been used in a large number of studies to classify term and preterm deliveries, [11,38]. They have also been useful for distinguishing between non-labour and labour events [11,38], irrespective of whether they were term or preterm. Moslem et al. [14] argue that they have been particularly useful in helping to identify important risk factors associated with preterm birth. The global accuracy of these studies varied from between 73% and 97%.

Baghamoradi et al. [39] used the TPEHG database [10] to compare sample entropy with thirty and three cepstral coefficients extracted from each signal recording through sequential forward selection and Fisher's discriminant. A multi-layer perceptron (MLP) neural network classified the feature vectors into term and preterm records. The results indicate that the three cepstral coefficients produced the best classification accuracy, with 72.73% (613.5), while using all thirty coefficients showed only 53.11% (610.5) accuracy. Sample entropy performed the worst with an accuracy of 51.67% (614.6). The results indicate that the sequential forward selection and Fisher's discriminant had the most effect on the accuracy because the thirty coefficients set only presenting a small improvement, in classification accuracy. Support Vector Machines (SVM) have featured in several studies, which include [12,13,14]. Many of them classify contrac- tions into labour or non-labour, using different locations on the abdomen. Majority voting (WMV) decision fusion rules, including a Gaussian radial basis function (RBF), form the basis for classification. The feature vectors include the power of the EMG signal, and the median frequency. The highest accuracy for a single SVM classifier, at one particular location on the abdomen, was 78.4% [12,13], whilst the overall classification accuracy, for the combined SVM, was 88.4% [14]. Finding the coefficients, for the decision boundary, occurs by solving a quadratic optimisation problem.

The k-NN algorithm has been used by Diab et al. [40] with an emphasis on Autoregressive (AR) modelling and wavelet transform pre-processing techniques. The study focused on classifying contractions into three types using data obtained from 16 women. Group 1 (G1), were women who had their contractions recorded at 29 weeks, and then delivered at 33 weeks; Group 2 (G2) were also recorded at 29 weeks, but delivered at 31 weeks, and Group 3 (G3) were recorded at 27 weeks and delivered at 31 weeks. Classification occurred against G1 and G2 and against G2 and G3 using, the k-NN algorithm combined with the pre-processing method of AR. As well as this, an Unsupervised Statistical Classification Method (USCM), combined with the pre-processing method of Wavelet Transform, was also used. The USCM adopted the Fisher Test and k-Means methods. The wavelet transform, combined with USCM, provided a classification error of 9.5%, when discerning G1 against G2, and 13.8% when classifying G2 against G3. Using AR, the k-NN provided a classification error of 2.4% for G1 against G2 and 8.3% for G2 against G3. In both classifications, the AR and k-NN methods performed better than the USCM. Furthermore, the classification accuracy for G1 and G2 was always lower than the equivalent G2 and G3 classifica- tions. This suggests that it is easier to distinguish between pregnancies recorded at different stages of gestation than it is to distinguish between the time of delivery.

Proposed System

The system used for automatic identification of the EHG signals is described using a block diagram shown in Figure 1.

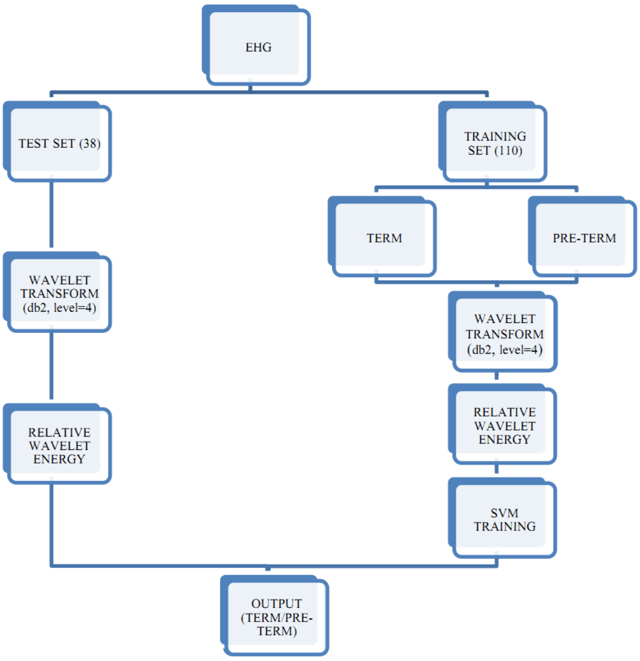

Figure 1. Block Diagram

Signal Acquisition

The uterine EHG signals of a total of 146 pregnant women were downloaded from Physionet. One fourth of the data records were separated into test set (36) and the rest (110) as training set. The training set was grouped further into four groups according to the time of recording (before or after the 26th week of gestation) and according to the total length of gestation (term delivery records— pregnancy duration >=37 weeks and pre-term delivery records— pregnancy duration < 37 weeks.

Feature Extraction

The dimension of the EHG signals is too high to be used directly for classification. Therefore it is important to apply feature extraction techniques in order to obtain informative features. Among all the feature extraction techniques used for signal processing, wavelet transform is found to be most successful. This is due to the reason that wavelet transform works in time and frequency domains. Therefore Discrete Wavelet Transform (DWT) is used to extract the features.

Feature Reduction

Further the features representing the burst of electrical activity are extracted by applying Relative Wavelet Energy (RWE) on the EHG signals. This feature reduction tools helps in further cutting down the feature vector matrix which is then sent for classification.

Classification

The classification stage is used to discriminate between different classes, term and pre- term pregnancy state. A classifier plays a very important role and thus it should accurately separate the data into the two groups. For this work Support Vector Machines (SVM) is used for classification purposes. The classifier is first trained using the training set and then tested using the test set.

II. METHODOLOGY

Wavelet transform

A crucial part of the EHG processing consists of transforming the information acquired from the signals into a small number of components which represent the uterine activity. Traditional Fourier transform methods (Fast Fourier transform and Short time Fourier Transform) have proved to be extremely insightful over the years as a feature extraction technique. However, there are various limitations while applying these techniques like they are not suitable to extract features localized simultaneously in time and frequency domain. Due to this reason they cannot be used to analyze transient signals especially when it is required to generate features for detection and discrimination for critical applications. Over the past several years, the methods based on Wavelet Transform (WT) (Stationary WT, Discrete WT, Wavelet Packet) have received a great deal of attention for extracting information from the EHG signals. This can be accounted to the Multi resolution analysis (MRA) which makes WT the most suitable candidate for analysis of frequency content of non-stationary events which is a prerequisite for EHG signals.

WT decomposes a signal into small waves with energy concentrated in time called wavelets. Wavelets are the scaled and shifted copies of the main pattern, so-called the mother wavelet. The mother wavelet function is defined by equation (1), where b is translation parameter and, a as scale parameter.

$$\Psi_{a,b} = \frac{1}{\sqrt{a}} \Psi \frac{(t-b)}{a}$$

DWT analyses the signal using MRA by decomposing the signal into approximation and detailing information by employing two functions: scaling and wavelet function as shown in equation 1. The approximation coefficient is subsequently divided into new approximation and detailed coefficients.

This process is shown in Fig. 2 which is carried out iteratively producing a set of approximation coefficients (CA) and detailed coefficients (CD) at four different levels of decomposition.

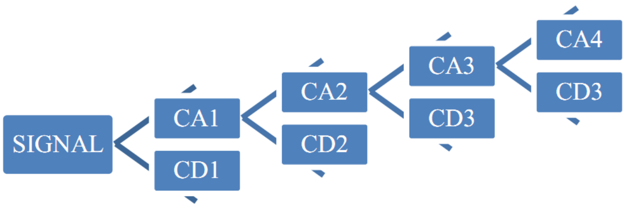

Figure 2. Decomposition

Relative Wavelet Energy

If the scaling functions and wavelets form an orthogonal basis, Parseval's theorem relates the energy of the signal x(t) to the energy in each of the components and their wavelet coefficients. The energy Ej of the detailed signal at each resolution level j is given by

$$E_j = \sum_k | d_{j,k} |^2$$

Total energy is given by

$$E_{Total} = \sum_{j=1}^{N+1} E_j$$

The wavelet energy can be used to extract only the useful information from the signal about the process under study. For this work the concept of relative energy has been used. RWE gives information about relative energy with associated frequency bands and can detect the degree of similarity between segments of a signal. RWE is defined by the ratio of detail energy at the specific decomposition level to the total energy. Thus the relative energy is given by:

$$RWE = \frac{E_j}{E_{Total}}$$

RWE resolves the wavelet representation of the signal in one wavelet decomposition level corresponding to the representative signal frequency. Thus this method accurately detects and characterizes the specific phenomenon related to the different frequency bands of the EHG signal. RWE gains an advantage over DWT based feature extraction in terms of speed, computation efficiency and classification rate.

Support Vector Machines

The approach of SVM is to find an optimal hyper- plane in the multi-dimensional space of features, which would separate the classes being considered with the largest distance (margin) to the nearest training data points. The data (input vectors) that ensure this safety margin are called the support vectors. This optimal hyper plane is constructed in such a way that it maximizes the minimal distance between itself and the learning set.

$$g(y) = \mathrm{sgn}\left(\sum_{i=1}^{ls} d_i \alpha_i K(y_i, y) + b \right)$$

Maximize

$$\sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} d_i d_j \alpha_i \alpha j\, K(y_i, y_j)$$

Subject to

$$\sum_{i=1}^{l} \alpha_i d_i = 0 \qquad 0 \le \alpha_i \le C \; for\; i = 1,2.....l$$

$$K(u,v) = \exp\left(-\frac{\| u - v \|^2}{2\sigma^2} \right)$$

III. CONCLUSION

In this paper DWT based feature extraction is incorporated to classify the EHG signals using Support Vector Machines based classifier. The RWE of different EHG signals were obtained which provided a compact and accurate feature space to achieve better classification rate and reduced computational load. Due to its memory efficient capability this concept can generalize the EHG processing to much larger datasets. The SVM based classifier presented has a good performance in classifying the 2 stages of labor and can be easily implemented on hardware for real time response. The most redeeming feature of proposed system is its capability to achieve excellent computational efficiency without any loss of information. This sets apart the system from the other automatic classifiers falling in the same levels of accuracy without any requirement of topnotch PCs. Owing to the suitably high accuracy achieved using the synergy of SVM and RWE technique, the methodology presented in this paper can be utilized for designing automatic EHG classifiers which can be used by the gynecologist for detecting premature birth risk.

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