Foetal Distress: A Review

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Abstract

Foetal behavioural features are the most relevant features of foetal physiology and pathology related to foetal heart rate (FHR) signals. FHR is used to examine foetal wellness and provides a support to clinicians to get rid of hypoxic condition during delivery. In routine, morphological features of FHR signals are observed by naked eye during clinical evaluation. This article reviews various features, like, morphological, time domain and nonlinear features, used to assist clinicians and/or expert systems for better evaluation of foetal well-being.

[1] INTRODUCTION

Foetal heart rate (FHR) monitoring, also known as cardiotocography (CTG), can assist obstetricians in foetal surveillance during pregnancy and labour [9,11,15]. Cardiotocograph, also known as Electronic Foetal monitor, is an electronic device used to records the FHR (cardio-tacho) and alterations in the uterine muscle tone curve (toco-dynamo) simultaneously and CTG is a graphical recording of foetal heartbeat and uterine Contraction(UC) by cardiotocograph .

The main purpose of foetal monitoring is to provide clinicians a way to detect hypoxic condition in foetuses in order to reduce unfavourable conditions of foetal and extreme obstetric intervention for assessing foetal well-being [12,21,22]. The knowledge, skills and experience of healthcare provider plays a vital role in interpretation of CTG signals to assimilate FHR traces in order to extract different features and patterns [12,9]. CTG interpretation is usually done by visual inspection by practitioners, which probably lacks objectivity and reproducibility and therefore suffers from both intra-observer and inter-observer variability [15,9]. Intra-observer variability means one person evaluates at different times and produce different results. Inter-observer variability means different persons observes at same time and produces different results [15,9]. Moreover, high false positive rate of the FHR signal results into increased rate of caesarean sections and unnecessary deliveries [15]. Researchers are trying to develop a computer-aided analysis systems that extract parameters from the FHR signals and assist clinicians in diagnosing foetal state [15].

The main aim of this study is to represent a various types of features that have been employed for assessment of foetal well-being in various research studies.

[2] Preprocessing

Preprocessing is mostly the first step in all biomedical signal processing applications. The values of extracted features depend a lot on this step and affects classification performance also. FHR signals are affected by various types of noises, such as, the displacements of the transducer, movements of both foetus and mother, stress due to labour-pain and others.

The main preprocessing steps include outlier detection and interpolation. A basic artefact rejection scheme is used on feature values those do not lie within range 5o to 200 by interpolation. Also, the missing beats in the signal should be interpolated. Small gaps are corrected by the cubic Hermite spline interpolation method, which has been proven to be sufficiently robust, as well, accurate. The signals with long gaps (>15 s) are simply ignore for the process of feature extraction. Final step is to apply detrending, which is removal of

trend of change in mean over time, over the FHR signals using second-order polynomials. Interested readers may refer article [1, 2, 11, 23] for further study on preprocessing.

[3] Feature Extraction

Feature extraction after signal preprocessing was done to interpret FHR signal and assessing foetal condition. There are various types of features being used to assess foetal state.

[3.1] Morphological Features

The internationally recognised Federation of Gynaecology and Obstetrics(FIGO) [5] and the National Institute for Health and Care Excellence (NICE) [14] have identified and explained baseline, acceleration, deceleration and variability as the major physiological features for foetal monitoring. These features provide information about the macroscopic properties and the changes in shapes of the FHR signals.

Baseline (BL) has more weightage among all other morphological features used in FHR pattern recognition because its value is used to calculate other morphological features also [4, 17, 20]. According to the Royal College of Obstetricians and Gynaecologists (RCOG), "Baseline is the mean level of the FHR when it is stable, i.e., excluding accelerations and decelerations. It is generally calculated over time duration of 5 or 10 minutes in terms of beats per minutes (BPM). This time period can be of any duration but not be less than 2 minutes otherwise baseline value is indeterminate.

Let assume an N sample FHR time series signal Y, where $Y = \{ y(n), n = 1,2 \dots N\}$. Virtual imaginary baseline ($\bar{y}$) is used to calculate the true baseline value and was computed in all accepted windows as

$$\bar{y} = \frac{\sum_{n=1}^{w} y(n)}{N}, \quad (1)$$

where w is the size of the window. Virtual baseline is used to define the maximum (H) and minimum (L) limits of FHR, where $H = \bar{y} + \alpha$ and$L = \bar{y} - \alpha$, and the computed baseline should be within this range. These limits are used to find a derived signal z as:

$$z(n) = \begin{cases} H & if\ y(n) > H \\ y(n) & if\ l \le y(n) \le H \\ L & if\ y(n) < L \end{cases}, \quad (2)$$

where n is current sample. Baseline in each window was calculated as:

$$Base\_win = \frac{\sum_{n=1}^{w} z(n)}{w}. \quad (3)$$

There is a one value of baseline for each sample, which is obtained by taking average of baseline values of all windows of a single recording.

To determine the boundaries L and H of FHR, the best value of constant α to be subtracted and added from the virtual baseline ($\bar{y}$) is choose experimentally. The results obtained are also compared with the experts opinion. Finally it is concluded that α= 8 BPM produced better results and best accuracy [16, 3].

Accelerations, another morphological feature, in the signal is defined as:

$$Acc_{count} = \exists y(n) \in Y, \sum_n ((y(n) \ge (Baseline + 15)) \,\&\, (D \ge 15)) \quad (4)$$

where Y is the signal, Baseline is the real baseline value of the complete signal, $y(n)$ represents the n^{th} element of y, D is the number in seconds. Thus the Acceleration count is incremneted for every x_i remaining above the baseline by 15 BPM or more for D duration.

Decelerations in the signal is defined as:

$$Dcc_{count} = \exists y(n) \in Y, \sum_n ((y(n) \le (Baseline - 15)) \,\&\, (D \ge 15)). \quad (5)$$

Here the count is incremented when $y(n)$ remains below baseline by 15 BPM or more for D number of seconds [14].

[3.2] Time Domain Features:

Let y(n), $n = 1, \dots, N$ be defined as the FHR signal. Significant time domain features for FHR signal, as in [24,25], are

Mean is defined as

$$\text{mean\_FHR} = \bar{y} = \frac{1}{N}\sum_{i=1}^{N} y(i). \quad (6)$$

Standard Deviation,

$$sd\_FHR = \sqrt{\frac{\sum_{i=1}^{N}(y(i)-\bar{y})^2}{N-1}}. \quad (7)$$

Long-term Irregularity(LTI) is Interquartile range $\left[\frac{1}{4},\frac{3}{4}\right]$ of the series $lt(i)$ with $i = 1, 2, \dots, N-1$ and $lt(i) = (\sqrt{y^2(i) + y^2(i+1)})$,

$$LTI = IQR(\sqrt{y^2(i) + y^2(i+1)}) \quad (8)$$

Long-term variability (LTV or delta) is the average of difference between the maximum and minimum values in a 60-s block, i.e., constitutes of 240 samples if FHR signal is sampled at 4 HZ. Delta is computed over block of one minute signal duration. M is the duration of FHR signal in minutes. Max(y(i)) and min(y(i)) are maximum and minimum value of signal in i^{th} block.

$$\text{delta} = \frac{1}{\text{M}}\sum_{\text{i}=1}^{\text{M}}\left[\max_{\text{i}\in\text{M}}(\text{y(i)}) - \min_{\text{i}\in\text{M}}(\text{y(i)})\right] \quad (9)$$

Short-term Variability (STV) is defined as regular variation in successive inter-beat intervals and significant to analyse foetal reactions to internal or external stimuli. Though important, this parameter is difficult to get interpreted correctly through naked eye. The method to calculate STV depends upon signal acquisition approach, whether external or internal. In case of internal recordings, beat-to-beat variability is directly estimated, whereas correlation-based estimation technique has to be used for external recordings. In general, a healthy autonomic nervous system (ANS) has a large STV value and can provide a support in diagnosing foetal health [6]. To compute the average value of i^{th} block, sm(i), where $i = 1,2 \dots N/10$, the FHR signal was considered into 2.5 Sec blocks, i.e., 10 samples if signal is sampled at 4 HZ. The $sm(i)$ calculation depends on the change in interval of vector [2,19].

$$STV = \frac{1}{24*M}\sum_{i=1}^{24*M}(sm(i+1) - sm(i)) \quad (10)$$

FHR variability (FHRV) in short and long terms has significant role in clinical settings [13].

Interval Index(II) reflect changes in FHR variability and average. [13].

$$II = \frac{STV}{STD(sm(i))} \quad (11)$$

[3.3] Nonlinear Features

Approximate Entropy (ApEn), Sample Entropy (SpEn) and Lempel-Ziv Complexity (LZV) are among some of the important nonlinear features. They are robust in assessing signal complexity (or irregularity) and are calculated by direct signal estimation [8].

Approximate Entropy measures uniformity, correlation and persistence of a signal. FHR signals with more randomness has a relatively larger ApEn, whereas snmaller value of ApEn indicates signal is repetitive and more predictable. Given N data points, y(1), y(2), …, y(N), two parameters tolerance (r) and embedding dimension (m) must be fixed. First of all, vector sequences from u(1) through u(N-m+1) from {y(i)} is defined

$$u(i) = \{y(i), y(i+1), \dots . y(i+m-1)\} \quad (12)$$

These vectors has m consecutive values starting from i$^{\text{th}}$ index .Next, define for each i, $1 \le i \le N - m + 1$,

$$C_i^m(r) = \frac{(number\ of\ j\ suc\square\ t\square at\ \ d[u(i),u(j)]\le r)}{N-m+1} \quad (13)$$

Where d [u (i), u (j)] is defined for vectors u (i) and u (j) as in [7]

$$d[u(i),u(j)] = \max_{k=1,2\dots m}(|y(i+k-1)| - |y(j+k-1)|) \quad (14)$$

$where\ j = 1,2 \dots n - m + 1$ [7]. Now, from $C_i^m(r)$ we find the value of $\emptyset^m(r)$as [7]

$$\emptyset^m(r) = \frac{\sum_{i=1}^{N-m+1}\log\left(C_i^m(r)\right)}{N-m+1} \quad (15)$$

Estimated ApEn (m, r, N) for N signal points is

$$ApEn(m,r,N) = \emptyset^m(r) - \emptyset^{m+1}(r) \quad (16)$$

Sample Entropy is also computed using formula (15) except one change in formula (13) that $i \neq j$. Sample Entropy avoids counting self-matches for reduction in bias as in Approximate Entropy. The values of r = 0.2 and m=2 are usually considered for calculation. $ApEn$ and $SpEn$ produce good statistical validity for these values for both clinical and theoretical analysis [10, 8, 24].

Lempel-Ziv Complexity (LZC) estimates the reoccurring patterns irrespective of time in FHR series. A periodic signal having a low value of LZC has same reoccurring pattern. Aperiodic signals have rarely reoccurring pattern and so have large value of LZC [19].

A new sequence (U) denoted as u(1), u(2), ...u(n) is from series y(1), y(2), ..., y(n) as

$$u(i) = \begin{cases} 1, & y(i+1) > y(i) \\ 0, & y(i+1) \leq y(i) \end{cases} \quad (17)$$

The algorithm counts the same patterns in u. The value is incremented by one for each new pattern. When the last element of the U occurs, c (n) is increased by 1, traditionally. C (n) depends on the length of the original signal. Now, to remove dependency on the length of signal is removed b the normalization as described below [19, 18].

$$C(n) = \frac{c(n) * log_2(n)}{n} \quad (18)$$

[4] Conclusion:

The article studies the features used in time-series analysis and for a specific problem of FHR. With morphological features and time domain features, many nonlinear features based on various entropy definitions are studied. Corresponding literature is reviewed.

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