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Investigating an Optimal Signal Epoch Length for Cardiotocographic Classification

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Abstract: This work focuses on investigating an optimal foetal heart rate (FHR) signal segment to be considered for automatic cardiotocographic (CTG) classification. The main idea is to evaluate a set of signal segments of different length and location based on their classification performance. For this purpose, we employ a feature extraction operation based on two signal processing techniques, such as the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and time-varying autoregressive modelling. For each studied segment, the features are extracted and evaluated based on their performance in CTG classification. For the proposed evaluation, we make use of real CTG data extracted from the CTU-UHB database. Results show that the classification performance depends considerably on the selected FHR segment. Likewise, we have found that an optimal FHR segment for foetal welfare assessment during labour corresponds to a segment of 30 minutes long.

Keywords: Cardiotocograph, Foetal heart rate signal, Time-varying autoregressive spectrum, ICEEMDAN

1 Introduction

In current clinical practice, foetal welfare assessment during labour commonly depends on the analysis of particular morphological patterns involved in the foetal heart rate (FHR) and uterine contraction (UC) signals. These signals, acquired through a Cardiotocograph (CTG), are assessed by the naked eye following recommendations of proposed CTG guidelines [1]. Unfortunately, the CTG interpretation by this methodology is difficult for the clinical staff, which has shown high intra- and inter-observer disagreement leading to very low specificity.

In this context, several signal processing approaches have been proposed in order to extract more significant information from the FHR signal and thereby improve the CTG signal interpretation [2, 3]. Most of the proposed approaches are based on extracting signal features on a particular FHR segment where the features can be computed, also called as FHR *epoch*.

Recent clinical research [4, 5] emphasizes that each foetus presents its own behaviour and control, which is modulated by the autonomic nervous system (ANS). Besides, the foetal condition depends on how it is compensating and modulating itself over time, whose status can change from one time instant to another. In the presence of this non-stationary phenomenon, the selection of an optimal FHR epoch is challenging because it requires to be long enough for the data characterization, but at the same time short enough in order to identify the current foetal status.

Several FHR signal epochs, defined by their length and location, have been studied in the literature [2], however, there is no precise definition for an optimal FHR epoch to be considered for the analysis of the CTG recording.

This approach aims to investigate an optimal FHR epoch for an automatic CTG analysis. For this purpose, following [6], we employ a signal feature extraction strategy based mainly on two signal processing techniques, such as the Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) and time-varying autoregressive (TV-AR) modelling. In this work, we examine different FHR segments, which are evaluated according to their performance in CTG classification based on a support vector machine (SVM) classifier. The proposed evaluation has been performed on real CTG data extracted from the open-access CTU-UHB database [7]. Results show that the classification performance depends considerably on the selected FHR segment, and a segment of 30 minutes long can be considered as an optimal FHR epoch for an automatic CTG analysis.

2 Methodology

The proposed approach makes use of the signal feature extraction and evaluation strategy presented in [6]. This section first presents a brief explanation concerning the CTG dataset used in this work (Section 2.1). Then, Section 2.2 presents a summary of the FHR signal feature extraction strategy applied to the CTG signal.

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2.1 Dataset selection

For the evaluation of the proposed approach, we make use of real CTG data extracted from the CTU-UHB database [7], which consists of 552 CTG recordings sampled at 4 Hz. From this database, we consider a dataset divided into two classes: normal and acidotic conditions. Following [8], these two classes have been selected according to the foetal outcome information, particularly the pH and BDecf parameters. The normal class includes CTG recordings with values of pH < 7.05 and BDecf ≥ 12, whereas the acidotic class involves recordings with values of pH > 7.20 and BDecf < 12, whose values have been set according to [9]. As a result, the dataset includes 354 normal and 18 acidotic cases.

2.2 Feature extraction strategy

The proposed approach is based mainly on two signal processing techniques: ICEEMDAN and TV-AR modelling. The performed feature extraction strategy, explained in detail in [6], can be summarized as follows.

First, in order to deal with signal loss and outliers resulting from the signal acquisition procedure, we perform a signal preprocessing step, which is applied to the FHR and UC signals. For the FHR signal, we employ the artefact rejection method proposed by [10], which allows removing inconsistent FHR signal values (outside the range between 50 bpm and 210 bpm) and interpolate loss-of-signal data ≤ 75 s. For the UC signal, we interpolate loss-of-signal ≤ 25 s in length, and then, the signal is filtered by a moving average filter of 15 s window length [6].

Second, we identify FHR decelerations, which are analysed together and independently from the entire signal. The FHR decelerations are considered as one of the most significant CTG signal patterns to assess the foetal condition. However, at the same time, they are one of the most challenging patterns to interpret by clinicians [11]. For this operation, we make use of a progressive baseline (PBL) and a *floating-line*, which are obtained by a non-linear median filter computed with a window of 400 s and 10 s long, respectively.

Third, the preprocessed FHR signal is detrended by the subtraction operation between the preprocessed FHR signal and the floating-line. The resulting detrended FHR signal is finally decomposed into intrinsic mode functions (IMFs) by ICEEMDAN in order to study FHR signal dynamics resulting potentially from the modulation of the ANS. These decomposed components are analysed in the time-domain as well as in the frequency-domain by using TV-AR spectral based analysis. The main advantage of the proposed decomposition operation is that ICEEMDAN provides less complex signal data involved in the IMFs. These IMFs are better suited for the subsequent spectral analysis performed by parametrical modelling (e.g. TV-AR modelling), because the analysis focuses on tracking only one main frequency component of interest for each IMF over time. Following [12], the ICEEMDAN computation was performed by using a noise standard deviation Nstd $= 0.03$ and 50 realizations. The TV-AR spectrum was computed by using a model order $p = 6$ and a forgetting factor set to 0.99 [6, 8].

The feature extraction is performed on the obtained indicators such as the FHR signal, detrended FHR signal, PBL, IMFs, and TV-AR spectrum (total energy, energy of the main component, and frequency of the main component) computed from each IMF. For each indicator, we calculate seven statistical coefficients commonly used in CTG analysis: arithmetic mean (μ), median (M), standard deviation (σ), mean absolute deviation (mad), root mean square (RMS), sample entropy (SampEn), and approximate entropy (ApEn). These statistical coefficients are computed independently during FHR decelerations (D), resting periods (R), and entire FHR segment (S). As a result, the complete set of features consists of 279 features extracted from R and S individually, and 213 features extracted from D.

For a more detailed explanation of the feature extraction operation used in this work, please refer to [6]. Codes involved in this approach have been implemented in Matlab® environment version 2018b.

3 Results

As explained in Section 1, we propose to investigate an optimal FHR epoch that can be appropriate for an automatic CTG analysis. The main idea is to study how the CTG classification performance varies when considering different FHR signal segments. For this purpose, we study different FHR epochs of variable length and location inside the last 60 minutes of recording before delivery. These epochs consist of FHR data of 20, 25, 30, 35, 40, 45, 50, 55, and 60 minutes long, sliding in steps of 5 minutes. It is important to note that the epoch of 60 minutes long involves the complete studied range; therefore, it does not slide.

Fig. 1 shows a graphic representation of the proposed study, where the examined FHR epochs are defined by an initial (t_i) and a final (t_f) time. In this figure, $t = 0$ corresponds to the delivery time, and the time $t = 60$ means one hour before delivery.

For the analysis of the studied FHR epochs, firstly, the complete set of features is extracted for each epoch. Secondly, we apply a Wilcoxon rank-sum test to consider only significant

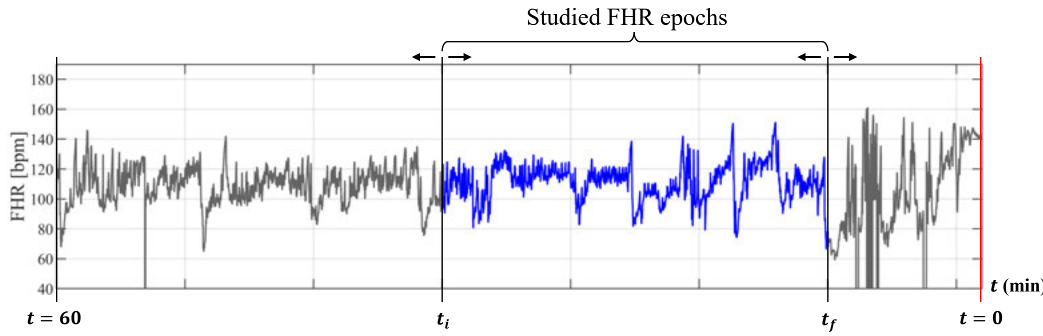

Fig. 1: Representation of studied FHR epochs of variable length and location.

Tab. 1: Studied FHR epochs defined by their initial (t_i) and final (t_f) time.

Epoch	t_i (min)	t_f (min)	QI (%)	Epoch	t_i (min)	t_f (min)	QI (%)	Epoch	t_i (min)	t_f (min)	QI (%)
Ep_1	60	40	75.9	Ep_{16}	55	5	81.6	Ep_{31}	40	20	80.7
Ep_2	60	35	73.5	Ep_{17}	55	0	84.3	Ep_{32}	40	15	77.7
Ep_3	60	30	72.6	Ep_{18}	50	30	73.9	Ep_{33}	40	10	76.7
Ep_4	60	25	81.1	Ep_{19}	50	25	75.2	Ep_{34}	40	5	85.7
Ep_5	60	20	81.1	Ep_{20}	50	20	79.1	Ep_{35}	40	0	84.2
Ep_6	60	15	79.7	Ep_{21}	50	15	73.1	Ep_{36}	35	15	83.2
Ep_7	60	10	81.1	Ep_{22}	50	10	77.7	Ep_{37}	35	10	82.6
Ep_8	60	5	81.5	Ep_{23}	50	5	80.4	Ep_{38}	35	5	82.8
Ep_9	60	0	80.4	Ep_{24}	50	0	78.1	Ep_{39}	35	0	81.4
Ep_{10}	55	35	80.8	Ep_{25}	45	25	76.1	Ep_{40}	30	10	83.8
Ep_{11}	55	30	76.9	Ep_{26}	45	20	78.9	Ep_{41}	30	5	86.7
Ep_{12}	55	25	78.0	Ep_{27}	45	15	74.9	Ep_{42}	30	0	**89.9**
Ep_{13}	55	20	80.6	Ep_{28}	45	10	79.5	Ep_{43}	25	5	82.3
Ep_{14}	55	15	77.9	Ep_{29}	45	5	84.1	Ep_{44}	25	0	79.1
Ep_{15}	55	10	78.7	Ep_{30}	45	0	81.6	Ep_{45}	20	0	83.4

features (p-value $< .05$) for the analysis. Then, the features are evaluated based on a recursive feature selection strategy proposed in [6] by using a SVM classifier. As a metric of classification performance, we employ the geometric mean between the sensitivity (Se) and specificity (Sp), which is considered as an appropriate indicator of quality ($QI = \sqrt{Se \cdot Sp}$) for imbalanced data [13].

Table 1 displays the results obtained from the previous operation, which shows the classification performance (QI) achieved for each studied FHR epoch. As can be observed in the table, we have examined 45 FHR epochs in total, which are defined by t_i and t_f.

Results show that the classification performance can vary considerably from one FHR epoch to another. The lowest performance (72.6%) has been achieved by Ep_3, which corresponds to a signal segment between 60 and 30 minutes before delivery. On the contrary, the highest classification performance (89.9%) has been achieved by Ep_{42}, epoch corresponding to the last 30 minutes before delivery. According to the obtained results, a FHR segment of 30 minutes long can be considered as an optimal epoch for CTG analysis.

The obtained results coincide with FHR segment lengths commonly examined in CTG guidelines for the assessment of several patterns such as increased FHR variability, sinusoidal and pseudosinusoidal patterns, prolonged decelerations, and contractions [1]. Besides, these guidelines indicate that the re-evaluation of the CTG recording should be performed at least every 30 minutes.

It is important to note that in [6, 14], the feature extraction strategy slightly differs from the operation performed in this work. In those approaches, we had first computed the indicators (e.g. PBL, floating-line, and IMFs), and then they were segmented to select an optimal epoch. Consequently, the studied FHR segments could involve information from previous FHR samples because of the memory required from the employed processing methods. Nevertheless, in those works, a precise epoch length was not critical because we had focused on the selection of an optimal set of features according to their contribution to CTG classification.

Considering that the goal of this work is to identify an optimal FHR epoch where the features can provide a higher classification performance, unlike the mentioned works, we first segmented the FHR signal, and then we compute the indicators. As a result, we obtain FHR segments that do not involve information from previous FHR samples. This update in the analysis strategy explains why the epoch between $t = 35$ and $t = 0$ does not coincide with the results obtained in [6].

4 Conclusion

Results show that the classification performance depends considerably on the selected epoch. Particularly, the maximal classification performance was achieved by considering an epoch of 30 minutes long just before delivery. Therefore, an automatic FHR analysis during labour should consider a window of 30 minutes long to assess foetal welfare.

These results coincide with FHR epoch lengths recommended in CTG guidelines for the assessment of several patterns [1]. Besides, these guidelines recommend a re-evaluation of the CTG recording at least every 30 minutes. However, in order to validate our obtained results, more investigation is required, which should include different computer-based classifiers, a study of more class formation criteria, and analysis of more CTG recordings from different databases.

Author Statement
Conflict of interest: Authors state no conflict of interest.

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