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INTELLIGENT FEATURE EXTRACTION IN FETAL HEART RATE SIGNAL

Correct classification of deceleration patterns in fetal heart rate signal is crucial issue for determining the fetal intrauterine distress of the fetus. Each type of deceleration has different physiological background, which implies different medical procedures. Therefore great emphasis have been put on formal description of deceleration features provided by FIGO guidelines. Patterns lasting less than two minutes are divided into two classes: episodic decelerations and periodic ones. Periodic patterns are characterized by correlation with uterine contraction, while episodic decelerations do not show such relation. The research material includes 101 cardiotocographic records of total duration of 285 hours, the clinical experts selected 383 patterns for further classification. Nineteen different parameters of quantitative description of deceleration were used as the input variables of the classification system. It turned out that there was a group of 11 parameters which can be omitted because they have very weak influence on the classification process. Quality indices of neural networks (from 93 % to 99 %) and the ROC curve indexes (from 0,9863 to 0,9944) explicitly show that the proposed networks are very efficient for the deceleration classification process.

1. INTRODUCTION

In present-day obstetrics the biophysical fetal monitoring is based on cardiotocography (CTG). It consists in acquisition of fetal heart activity and uterine contraction signal. In quantitative approach fetal heart activity is represented by the fetal heart rate (FHR) signal. The FHR is characterized by two main components: baseline (BL) and accelerations and decelerations patterns (A/D). Both baseline and transient increase and decrease in fetal heart rate (accelerations and decelerations) have important prognostic meaning because they give information about the fetal condition. In this work we concentrate on recognition and classification of deceleration patterns, which are considered as suspicious features of FHR trace and usually give a proof of the intrauterine distress.

Automatic classification of decelerations is very difficult to accomplish. The main reason is the imprecise, from an algorithmic point of view, guidelines which define deceleration patterns and their classes. These guidelines were defined by physicians and they are sufficient for visual analysis only. Their formalization is quite difficult but it is necessary for computerized systems. Considerable high interobserver disagreement as regards the pattern evaluation is additional problem, which makes verification of the developed decision system difficult.

Regardless many difficulties, attempts leading to automation of detection and classification of

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decelerations process have been taken up. Basic criteria coming from earlier FIGO guidelines [2] and relationship between parameters of deceleration and associated uterine contraction were used [1]. The other approach [4] is based on simple linear decision system which makes the classification. In our research and in [6] artificial neural networks were used for deceleration classification. Additionally, a great emphasis have been put on formal description of deceleration features provided by new obligatory guidelines [5].

2. METHODS

According to the report [5], the decelerations are transient patterns of fetal heart rate slowing below the baseline level of more than 15 bpm and lasting more than 15 s and not longer than 10 min. Decelerations with duration more than two minutes, regardless of others features, are called as prolonged. Patterns lasting less than two minutes are divided into two classes: episodic decelerations and periodic ones. Periodic patterns are characterized by correlation with uterine contraction, while episodic decelerations do not show such relation. Additionally, the analysis of the periodic deceleration in relation to its position to the uterine contraction can classify deceleration as early or late. However, this type of classification is not a subject of this work, and it will be made in further research.

We distinguished three phases within the deceleration pattern: onset, nadir and recovery (Fig. 1). Defining boundaries for each phase is very important and quite complex task. We calculate set of parameters describing distribution of FHR samples within deceleration. These parameters are inputs for the decision function which determines not only the start and end of deceleration but also the start and end of the nadir phase. We have to admit that nadir is wider concept than the lowest point of deceleration only. The nadir represents a group of FHR samples placed at the “bottom” of deceleration.

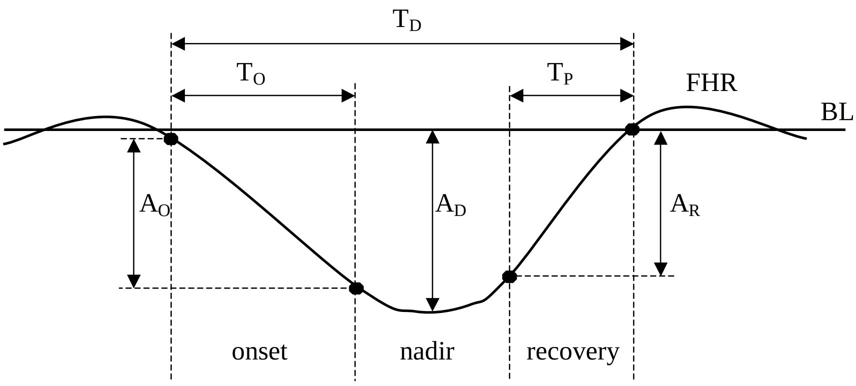

Fig. 1 Example deceleration with marked basic parameters. T_D – duration of deceleration pattern, T_O – duration of onset phase, T_R – duration of recovery phase, A_D – maximal difference between FHR and BL signals within deceleration pattern, A_O – difference between values of samples at the start and at the end of the onset phase, A_R – difference between values of samples at the start and at the end of the recovery phase.

According to the guidelines [5], during classification decelerations into periodic and episodic, the most important is the analysis of the shape of the onset of FHR signal within the pattern. If the onset is abrupt with duration less than 30 s it should be classified as episodic (Fig. 2). Whereas gradual onset (lasting more than 30 s) is a reason to classify this deceleration as a periodic one (Fig. 3). According to [3, 6] during classification we have to concern the shape of the analysed pattern. Characteristic feature in case of periodic deceleration, despite its gradual onset, is the uniform shape being something like mirror image of the uterine contraction. In case of the episodic deceleration, despite abrupt onset, it should be taken into account the absence the of uniform shape and occurrence of pseudo-accelerations before and after the pattern.

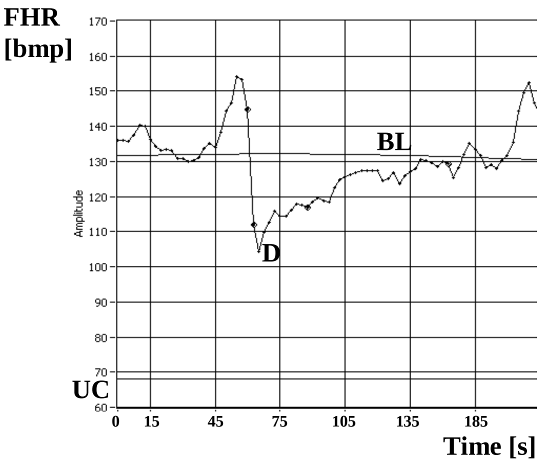

Fig. 2 Example of CTG trace with estimated baseline (BL) and an episodic deceleration event (D), which nadir is placed near 60 sec. There is no uterine contraction activity

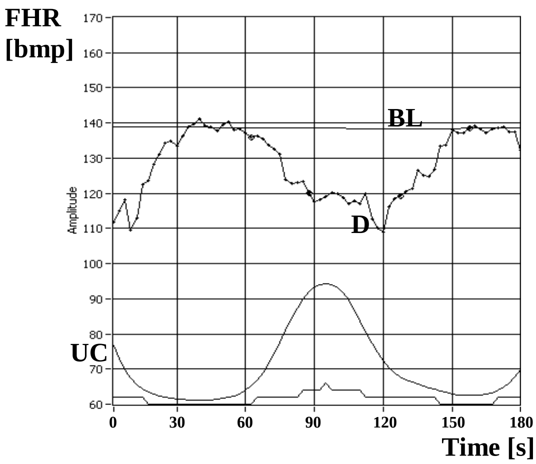

Fig. 3 Example of CTG trace with estimated baseline (BL) and a periodic deceleration event (D), which nadir is placed near 120 sec. There is a good quality signal of uterine contraction activity at the bottom.

During development of the system for deceleration classification, all the medical guidelines have to be taken into consideration. In first stepe the set of parameters, which quantitatively describes all the individual features of the shape of deceleration ought to be establishes very carefully. Basic parameters are: duration of deceleration pattern, area of the event, speed of onset, speed of recovery, duration of the onset and recovery phase. Quite often the more complex parameters are used like the mean value and the standard deviation of FHR samples. These parameters relate to both a whole analysed pattern and just specified part of deceleration.

The research material includes 101 cardiotocographic records of total duration of 285 hours. There were 2384 deceleration patterns detected by the MONAKO computer-aided fetal monitoring system (ITAM Institute, Zabrze). From the recognized events, the clinical experts selected only 383 patterns for further classification. Rejected decelerations were mostly the prolonged ones, which originally were not involve in the classification process at that phase. Remaining decelerations were rejected because of bad quality of FHR signal within them or unclear expert evaluation. Clinical experts were instructed to choose patterns, which represent very typical features. Each of 383 decelerations was assigned into one of two classes: periodic (55) or episodic (328). After classification, the measurements of 19 different features of quantitative description of deceleration were done. The determined parameters were the input variables of the classification system.

Artificial neural networks, which popularity in computer-aided medical decision systems is still rising [6], has been chosen as a classification system. During this research the Statistica Neural Networks 7.1 (Statsoft Inc.) software was used. Various available architectures of networks were tested. To find the optimal set of parameters the number of inputs were changing during experiments. It turned out that the best were the networks with radial basis functions (RBF) and multilayer perceptrons (MLP). The RBF networks were learned using the algorithms: k-means – for obtaining weights of neurons, k-nearest neighbour – for obtaining radii of neurons, and pseudo-invert (linear least squares optimization) – for obtaining weights of output neuron. The MLP networks were learned in few phases using the algorithms of back propagation and conjugated gradient descent.

For taking decision about the class membership, it has been assumed that the level of acceptance threshold and the level of rejection threshold are equal. All the deceleration patterns were randomly divided into three subsets for: learning, validation and testing. This was made in a such way that proportion among numbers of cases in each subset was 2:1:1. Although that division was random, the proportion between class sizes in each subsets was constant.

3. RESULTS

Table I presents parameters of three neural networks, whose results were the best. Quality of network for given data subset is defined as a proportion between the number of decelerations correctly recognized by the network to the number of all decelerations in the subset. The ROC curve summarizes the performance of a two-class classifier. The index of the ROC curve is the area under the curve. For the ideal classifier it is equal to one. The MLP network (8:8-16-1:1) appeared to be the best one, its quality in each subset was higher than 95 % and its ROC curve index has a value of 0,9944.

Tab. I Quality and the ROC curve indices of the proposed neural networks

Type and network architecture	Neural Network Quality			The area under the ROC curve
	Learning subset	Validation subset	Testing subset	
RBF 15:15-30-1:1	96 %	99 %	94 %	0,9875
MLP 8:8-16-1:1	98 %	99 %	95 %	0,9944
RBF 17:17-30-1:1	95 %	98 %	93 %	0,9863

Network architecture – number of inputs: input neurons-hidden neurons-output neurons: number of outputs

The confusion matrix for each of proposed neural network is shown in Table II. As it can be seen, the three neural networks are very efficient in classification of the episodic decelerations. Number of unrecognised episodic decelerations at the level of 4 or 5 is a very good result in comparison to the total number of 328 decelerations in this class. However, for the periodic decelerations the obtained results are not so satysfying. The RBF networks did not recognize respectively 10 and 13 decelerations classified by the experts as a periodic ones in comparison to the number of 55 decelerations in this class. The MLP network did not recognize 5 decelerations classified by the experts as periodic. Table III summarizes the quality of the best network (MLP 8:8-16-1:1) for classification of decelerations in comparison to the classification made by clinical experts.

Tab. II Confusion matrixes for final neural networks

Type and network architecture	Decelerations recognized by network as	Decelerations classified by expert as	
		periodic	episodic
RBF 15:15-30-1:1	periodic	45	4
	episodic	10	324
MLP 8:8-16-1:1	periodic	50	4
	episodic	5	324
RBF 17:17-30-1:1	periodic	42	5
	episodic	13	323

Network architecture – number of inputs: input neurons-hidden neurons-output neurons: number of outputs

Tab. III Deceleration classification for the best network – MLP 8:8-16-1:1

Type of deceleration	N	TP	FP	Sensitivity	PPV
periodic	55	50	4	90,90 %	92,59 %
episodic	328	324	5	98,78 %	98,48 %

Sensitivity and PPV (positive predictive value) are defined as TP/N and TP/(TP+FP) respectively, where TP is the number of true positives recognized, FP is the number of false positives recognized, and N is the number of positives classified by expert.

4. DISCUSION

The proposed parameters, which quantitatively describe individual features of deceleration shape, were chosen correctly. Quality indices of neural networks (from 93 % to 99 %) and the ROC curve indexes (from 0,9863 to 0,9944) explicitly show that the proposed networks are very efficient for deceleration classification process. It is important, that the best artificial neural networks did not need all of the 19 input parameters. For example, for the MLP network eight of them were enough. There is a group of parameters which can be omitted because they have very weak influence on the classification process. Similar conclusion have been found in [6], where 20 parameters were proposed but finally only four of them were used.

In everyday clinical practice the number of observed periodic decelerations is much less then the number of the episodic ones. This proportion is reflected in our research material. Such difference can disturb the learning process of network. Neural network much better learns this class which has more cases. Unfortunately, results from Table II show that, like in [6], this disadvantageous situation can take place. Even for the best network (MLP 8:8-16-1:1) this situation occurred. Values of its sensitivity (periodic – 90,90 %; episodic – 98,78 %) and its PPV (periodic – 92,59 %; episodic – 98,48 %) explicitly show that network better learned to recognize the episodic decelerations, which were frequent in given data . Equal sizes of each class could prevent from this situation. But from the other side, it is recommended that proportion between sizes of classes should reflect the real situation. Another way to solve this problem could be the setting alternative acceptance/rejection threshold in order to prefer the periodic decelerations. This approach will be our next research step on improvement of neural networks for automated deceleration classification.

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