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FUZZY PREDICTION OF FETAL ACIDEMIA

Cardiotocography is the primary method for biophysical assessment of a fetal state. It is based mainly on the recording and analysis of fetal heart rate signal (FHR). Computer systems for fetal monitoring provide a quantitative description of FHR signals, however the effective methods for their qualitative assessment are still needed. The measurements of hydronium ions concentration (pH) in newborn cord blood is considered as the objective indicator of the fetal state. Improper pH level is a symptom of acidemia being the result of fetal hypoxia. The paper proposes a two-step analysis of signals allowing for effective prediction of the acidemia risk. The first step consists in the fuzzy classification of FHR signals. The task of fuzzy inference is to indicate signals that according to the FIGO guidelines represent the fetal wellbeing. These recordings are eliminated from the further classification with Lagrangian Support Vector Machines. The proposed procedure was evaluated using data collected with computerized fetal surveillance system. The classification results confirmed the high quality of the proposed fuzzy method of fetal state evaluation.

1. INTRODUCTION

Cardiotocography (CTG) is a biophysical method for assessment of fetal state. It consists in recording of changes of the fetal heart rate (FHR) and analysis of their relation to fetal movements and maternal uterine contractile activity (UC). Proper cardiac function is an indicator of adequate fetal blood oxygenation and show that the central nervous system is intact and provides a good modulating control. Hence, the analysis of fetal heart rate is an essential element of the routine diagnostic method for evaluation of the fetuses during pregnancy and labour [6,8]. A graphical representation of FHR signal is subject to the interpretation of a physician, whose task is to identify and classify the recording features. The basal level of FHR signal (called baseline) and its variability in the aspect of transient increase (acceleration) or decrease (deceleration) is the primary subject of medical evaluation. Acceleration patterns, as the temporary increases of FHR in response to fetal movement, are the signs of fetal wellbeing, indicating the alertness of the central nervous system. Fetal distress is revealed by deceleration patterns, as temporary slowing of the FHR that is usually related to dangerous oxygen deficiency. Numerous attempts were made to formalize the criteria for FHR signals evaluation. Nevertheless, the clinical standards are in accordance with guidelines on antepartum electronic fetal monitoring introduced by FIGO (fr. Fédération Internationale de Gynécologie et d'Obstétrique) [10]. Visual analysis of FHR recordings obtained directly from bedside monitor printouts is very difficult even for experienced clinicians. Therefore it was replaced by automated computer analysis. The computerized fetal monitoring systems provide the quantitative description of the signals but the effective methods for the diagnosis support, are still the topic of research [2,4,7]. The paper presents the procedure of evaluating the risk of fetal acidemia with a two-step parametric analysis of FHR signal. In the first stage, the quantitative parameters of signals were classified using fuzzy scoring system, whose rule base was developed using the FIGO guidelines. The goal of the fuzzy evaluation was to confirm the fetal wellbeing with the highest certainty. In the second stage of classification, the FHR signal parameters were assessed with Lagrangian Support Vector Machines (LSVM) [9]. However, only the recordings previously classified as indicating the abnormal state of the fetus were classified. The fuzzy assessment of fetal state corresponds to the screening procedure, whose goal is to eliminate healthy patients from further medical diagnostics, while the second stage may be interpreted as a diagnostic test conducted by a clinical expert.

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The proposed procedure was evaluated using data obtained form the archive of computerized fetal surveillance system [5].

2. FIGO CRITERIA

In 1987 the FIGO committee provided guidelines to assist in the proper use of electronic fetal heart rate monitoring [10]. In accordance with the guidelines the FHR recording can be assigned to one of three classes, defining the fetal state as “normal”, “suspicious” or “pathological”. The interpretation is based on the quantitative analysis of parameters describing the fetal heart rate including baseline, acceleration and deceleration patterns and instantaneous fetal heart rate variability. According to FIGO guidelines the baseline is: “the mean level of the FHR when this is stable, accelerations and decelerations being absent”. Acceleration and deceleration patterns of FHR signal are defined as transient deviations from the baseline with established range of duration and amplitude. According to the FIGO definition the acceleration is recognized if the increase in FHR above baseline is ≥ 15 bpm, and lasting ≥ 15 s. Deceleration is a slowing of heart rate below the baseline level with an amplitude >15 bpm and lasting ≥ 10 s. The instantaneous variability refers to short-lasting changes of the fetal heart rate. There are two types of instantaneous variability: short-term, defining changes of intervals between two consecutive heart beats (called beat-to-beat variability), and long-term with periodical changes of beat-to-beat variability concerning both the direction and magnitude (called oscillations of FHR). To describe the short-term FHR variability we used the STV index [11], and analyzing the long term variability we distinguished different types of oscillations: “O_0”, with the amplitude from 0 to 5 bpm, “O_I” with the amplitude in the range (5, 10] bpm, and “O_{III}” with the amplitude > 25 bpm.

The assessment of the fetal state on the basis of FIGO criteria consists in identifying the features of the analyzed fragment of FHR signal. However, the archive of computerized fetal surveillance system contains values of parameters of quantitative description of signals calculated for the entire monitoring time. In particular, the number of identified acceleration (ACC) and deceleration patterns is given as the mean value and expressed as the number of patterns detected per one hour of recording. The FHR variability analysis includes also a percentage of each type of oscillation having amplitudes consistent with the ranges described in the guidelines. The descriptive assessment of decelerations defined by FIGO was replaced with an evaluation of three types of decelerations provided by the fetal monitoring system: type A (D_A) with amplitude > 15 bpm and duration ≥ 10 s, type B (D_B) with amplitude ≥ 10 bpm and lasting ≥ 25 s, and type C (D_C) with amplitude > 15 bpm, longer than 10 s and associated with uterine contraction. The proposed criteria for the classification of FHR recordings based on the FIGO guidelines are shown in Table 1.

Table 1. The classification of antepartum FHR signals according to FIGO guidelines.

Quantitative parameter	Normal	Suspicious	Pathological
Baseline [bpm]	[110, 150]	[100, 110) or (150, 170]	[0,100) or >170
Accelerations [1/h]	>12	(1.5, 12]	[0, 1.5]
Decelerations [1/h]	$D_A \in [0, 1.5)$ and $D_B=0$ and $D_C=0$	$D_A \geq 1.5$ or $D_B \in (0, 1.5)$ or $D_C \in (0, 1.5)$	$D_B \geq 1.5$ or $D_C \geq 1.5$
STV [ms]	[6, 14]	> 14	[0, 6)
Oscillations [%]	$O_0=0$ and $O_I \in [0, 40)$ and $O_{III} = 0$	$O_0 \in [0, 40)$ and $O_I \geq 40$	$O_0 \geq 40$

There is no other noninvasive diagnostic method that would provide the fetal state more reliable and accurate at the time of fetal monitoring. Real fetal state will be known only after the delivery. However, in perinatology it is assumed that the fetal state can not change rapidly during pregnancy, and therefore the retrospective analysis can be applied when assessing the quality of the fetal state evaluation. The retrospective analysis involves the assignment of the fetal outcome to fetal state at the time of FHR signal recording. Also a reverse process is possible, when the prediction of fetal outcome is made on the basis of the classification result of the FHR signal. The reference fetal outcome is assessed by clinicians after delivery mostly with a help of three attributes of the newborn: percentile of birth weight, Apgar score (as a result of subjective, visual assessment of the newborn) and measurement of the negative logarithm of hydronium ion activity (pH) in the blood from umbilical cord vein. In this work, we investigated the possibility of the prediction of acidemia risk, since low level of pH indicates an inadequate respiratory gas pressure in the blood of newborns and provides an objective sign of fetal hypoxia. The value of pH ≥ 7.20 indicates the fetal wellbeing, while pH < 7.10 represents an abnormal fetal state. Values in between are usually interpreted as the possibility of the fetal health risk.

3. FUZZY SCORING SYSTEM

The nature of the diagnostic scheme and a lack of strict boundaries between the values of parameters describing the FHR that could really differentiate between the fetal wellbeing and distress make the application of fuzzy inference [12] very promising for evaluating the FHR signals. An application of a fuzzy system in the process of FHR recordings assessment requires the definition of the rule base being important for the inference process. In our approach the fuzzy rules were constructed with FIGO guidelines. As the clinician diagnosis expressed in the form of natural language statements is difficult to process with the computer algorithm we proposed Fuzzy Scoring System (FSS) that models point scales. Point scales are commonly used by clinicians to provide the qualitative assessment of FHR recordings. In the classical point scale a certain number of points is assigned to a specific range of values of the particular FHR signal feature [3]. The resulting sum of points indicates the class of the recording. In FSS the strict ranges of parameter values are represented by fuzzy sets, while the relations between a given range and the assigned number of points correspond to fuzzy rules defined on the basis of FIGO guidelines. Consequently, the rule base of the FSS system consists of single input single output fuzzy rules (SISO) in the form:

$$\underset{1\le i\le I}{\forall} R^{(i)}: \ \mathbf{if}\ \left(x_{0j}\ \mathbf{is}\ A_j^{(i)}\right)\ \mathbf{then}\ y^{(i)} = p^{(i)}, \tag{1}$$

where: I denotes the number of rules, which is equal to the number of ranges of quantitative parameters of FHR signal distinguished by FIGO, x_{0j} is the input (j-th parameter of FHR signal), $A_j^{(i)}$ is the linguistic value of linguistic variable in the antecedent of the rule, represented by a fuzzy set with the membership function $\mu_{A_j}^{(i)}(x)$, $y^{(i)}$ is the rule output value and $p^{(i)}$ is the number of points assigned to a given range of the signal feature.

The input linguistic variables of the system are the FHR signal features: mean of baseline, accelerations, decelerations, STV and oscillations. The linguistic values of these variables are defined as fuzzy sets representing the ranges corresponding to given fetal state. The fuzzy sets are defined by the membership functions in the form of trapezoid (see Fig. 1), with parameters a, b, c and d. The values of parameters were acquired from basic statistics of the research material [1]. The b and c were defined respectively as lower and upper quartile of quantitative parameter measurements in a given range. The a and d were calculated using the assumption that the membership of the values, defining the boundary between classes of the FHR parameter, should be the same for both classes and equal to 0.5, hence:

$$a = 2 \cdot l - b, \quad d = 2 \cdot u - c. \tag{2}$$

An example of membership function defining the normal range of particular parameters quantitatively describing the FHR signal is shown in Figure 1.

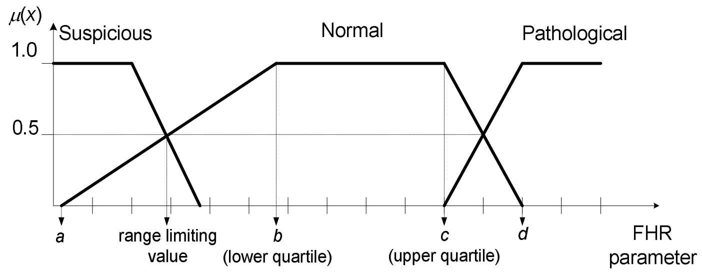

Fig. 1. An example of the membership function defining the normal range of a parameter quantitatively describing a given FHR feature.

The conclusions of the fuzzy rules are in the form of singletons, the location of which is defined with the assigned number of points. We used the following point scale in FSS:

- $p^{(i)} = -1,$ for the range corresponding to normal fetal state,
- $p^{(i)} = s, s \in [-0.5, 0.5],$ for the range corresponding to suspicious fetal state,
- $p^{(i)} = +1,$ for the range corresponding to pathological fetal state.

Introducing the number of points s from the interval [-0.5, 0.5] allows for different interpretation of ranges referring to suspicious fetal state. For $s < 0$ the ”suspicious” range is interpreted towards indicating fetal wellbeing, while for $s > 0$ as the fetal pathology. For $s = 0$ values of FHR parameters evaluated to be suspicious do not affect the final result of the signal classification. The crisp output value of fuzzy scoring system (FSS) is calculated as a weighted mean of points from all fuzzy rules:

$$y_0 = \frac{\sum_{i=1}^{I} \mu_{A_j}^{(i)}(x_0)\, p^{(i)}}{\sum_{i=1}^{I} \mu_{A_j}^{(i)}(x_0)} \tag{3}$$

The weights represent the level of association between the value of the particular quantitative parameter and the fuzzy rule. This association level is defined with the degree of membership of the parameter in the fuzzy set from the rule premise corresponding to a specific range of values. According to FIGO criteria (Table 1), there are 25 different ranges of values defined for quantitatively described features of FHR signal. Thus, the rules base of fuzzy system consists of $I = 25$ rules and each represents one of these ranges.

To estimate the performance of the system using standard indices of classification quality, such as sensitivity and specificity, and also to allow the next stage of the FHR signal analysis using support vector machines, we assumed that the final result of fuzzy reasoning was the assignment of the signal into two classes only, describing the fetal state as normal or pathological respectively. In the assumed point scale the sign of crisp output value of FSS system defines the assessment of the FHR recording. A positive or zero value indicates the pathology while the negative output represents the fetal wellbeing.

4. LSVM CLASSIFIER

Statistical analysis shows that the reassuring signal features in about 95% cases are confirmed by normal fetal outcome. Hence, fetal heart rate monitoring works well as a screening method. The first stage of the FHR signal analysis using fuzzy inference systems is applied for the same purpose. The task of the fuzzy system is to model the diagnostic procedure, which is used by a physician when assessing the FHR recording on the basis of FIGO recommendations. Consequently, the fuzzy classifier allows to indicate the FHR recordings confirming the absence of fetal hypoxia risk with high efficiency. Unfortunately, the recording features, which according to FIGO guidelines should be considered as pathological, may also characterize fetuses whose condition is normal. Therefore, the evaluation of the FHR recordings based only on a set of FIGO rules results in a high number of false positive assessments. To improve the effectiveness of the fetal state assessment a second stage of the FHR parametric analysis with support vector machines was introduced, and only recordings classified with fuzzy inference system as suspicious and pathological were evaluated. The SVM algorithm is based on the structural risk minimization, which leads to models of high learning quality and improved generalization capability. In practical applications, low computational cost of classifier is of special interest. For this reason, in the second stage of analysis of FHR recordings we applied a modified SVM algorithm - Lagrangian Support Vector Machines (LSVM) [9]. The LSVM solution has lower computational complexity than the original SVM while maintaining its high classification performance. The primary LSVM method formulates a linear classifier, nevertheless the nonlinear LSVM classifier can be obtained by application of kernel functions.

5. RESULTS AND DISCUSSION

The research material used in our experiments comprises the results of quantitative analysis of signals acquired from bedside fetal monitors. After removing the incomplete data as well as labor recordings, we obtained the database comprised of 189 antepartum records from 51 patients. The risk of acidemia was detected for seven fetuses from which a total number of 43 signals were analyzed. The main goal of the first stage of the classification was to identify the recordings indicating the fetal wellbeing. To achieve the minimum number of false-negative assessments we varied the parameter specifying the location of fuzzy set referring to suspicious fetal state. We changed values of *s* in the range of $[-0.5,+0.5]$ with the step 0.25. In the second stage of FHR signals analysis with the LSVM, a research material was divided into two equal parts: training and testing. The LSVM classifier was tested for 50 random divisions of the dataset. The parameters of LSVM algorithm providing the highest accuracy of fetal assessment were determined on the basis of the grid search method. The parameters γ and σ were searched among the values 10^{-3}, 10^{-2},…, 10^{5}. The convergence coefficient of the iterative algorithm for the Lagrange multipliers calculation was defined as $\alpha = 1.9/\gamma$. The LSVM algorithm was stopped if the maximum number of 100 iterations was achieved or if in the sequential iterations the change of the Lagrange multipliers was less than 10^{-5}. The data was normalized to the range $[-1,+1]$ before learning.

The classification accuracy was evaluated using the number of correctly classified cases expressed as the percentage of the testing set size (CC). Nevertheless, the minimal misclassification rate is not adequate to describe the quality of the results in medical applications. Consequently, to evaluate the fetal state assessment quality we applied the index QI, defined as the geometric mean of sensitivity (SE) and specificity (SP) $\left(\mathrm{QI} = \sqrt{\mathrm{SE} \cdot \mathrm{SP}}\right)$.

In the first step of our investigations we classified the FHR recordings using the proposed fuzzy system. The results (confusion matrix) are shown in Table 2 (column 1).

Table 2. The results of classification using FSS.

Before modification of ranges		After modification of ranges	
s = 0.50		*s* = 0.25	
34 [1)]	57 [2)]	43	71
9 [3)]	89 [4)]	0	75

[1)] TP - True Positive, [2)] FP – False Positive, [3)] FN – false negative, [4)] TN – True Negative

The classification accuracy was CC = 65.08% while the quality of classification QI = 69.42%. However, regardless of these values, the classification results are unsatisfactory, as we did not reach the objective of the first stage of FHR signals analysis, which was the confirmation of the fetal wellbeing with the highest efficiency.

To improve the quality of the classification, in particular to achieve zero false negative rate before the second stage of the analysis, it was necessary to modify the boundaries of ranges of FHR features. Therefore, we performed the simple statistical analysis of recordings retrospectively assessed as pathological. This analysis consisted in determining the maximum, minimum and median of parameters of FHR signal. For two parameters, STV and ACC, it was possible to identify new ranges of values corresponding to the risk of fetal hypoxia. For “pathological” recordings the STV index did not exceed 8ms, and the number of the detected acceleration patterns 13 per hour. These values were assumed to be boundaries of ranges representing the fetal wellbeing. Additionally, in the case of acceleration rate, we used the median of the ACC equal to 4 per hour as boundary between classes of suspicious and pathological FHR recordings. A similar analysis of recordings, which by the retrospective assessment indicated a normal condition of the fetus, showed that in 95% of cases the percentage of oscillation O_0 in the entire recording did not exceed 7%. Therefore, we modified boundaries for the O_0 as well. The resulting variability ranges of particular parameters are shown in Table 3.

Table 3. The modified variability ranges for particular descriptive parameters of the FHR signal.

Quantitative parameter	Normal	Suspicious	Pathological
ACC [1/h]	>13	(4, 13]	[0, 4]
STV [ms]	[8, 14]	>14	[0, 8)
O_0 [%]	0	[0, 7)	≥7

Strengthening the recordings assessment criteria allowed to improve significantly the quality of fuzzy classification (Table 2, column 2). We achieved sensitivity of 100%. Consequently, it was possible to eliminate from the second stage of classification the recordings that correspond to fetal wellbeing according to FIGO. The resulting classification accuracy decreased CC = 64.23%, but at the same time the classification quality increased QI = 71.67%. These results indicate higher level of sensitivity increase than the decrease of specificity. The second stage of the analysis of signal features using LSVM included only cases which were not assessed as normal during the fuzzy inference process. The results of the two-stage classification (Table 4) show the benefits of the application of the initial fuzzy analysis of FHR signals when assessing the fetal state.

Table 4. The results of FHR signals classification.

Performance index	LSVM $\gamma = 3.00$, $\sigma = 0.60$	FSS + LSVM $\gamma = 4.00$, $\sigma = 0.30$
QI	$83.3 \pm 5.57^{*)}$	85.3 ± 5.07
SE	73.3 ± 10.0	77.4 ± 9.71
SP	95.2 ± 2.23	94.3 ± 2.63
CC	90.3 ± 2.19	90.6 ± 2.29

$^{*)}$ mean value ± standard deviation

A combination of the FSS and the LSVM procedures resulted in increasing the classification sensitivity. The increase in sensitivity was accompanied by a decrease in specificity, however the final classification quality improvement measured with QI was obtained. A slight increase of classification accuracy was noticed as well. Higher sensitivity and lower specificity rates indicate that the initial fuzzy scoring of FHR recordings allows for improved detection of fetuses at risk at the expense of a slight increase in the number of unnecessary obstetric interventions (false alarms).

6. CONCLUSIONS

In the presented work we investigated the possibility of predicting the risk of fetal acidemia using the results of the fetal heart rate signal analysis. The recordings were assessed on the basis of the two-stage classification process. The first stage consisted in the evaluation of FHR recordings with fuzzy scoring system, whose rule base was determined according to criteria defined by the FIGO. The primary objective of the first stage of the classification was to eliminate from further diagnostic process recordings that represent the fetal wellbeing. In the second stage, only recordings previously classified as indicating the abnormal state of the fetus were analyzed. The final assessment was obtained by applying the nonlinear Lagrange Support Vector Machines. The results of experiments showed the improvement of the quality of fetal state assessment when using two-step analysis of FHR recordings in comparison to single-step evaluation on the basis of LSVM only. The obtained results indicate high effectiveness of the proposed method in the assessment of the risk of fetal hypoxia.

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