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FUZZY SYSTEM FOR EVALUATION OF FETAL HEART RATE SIGNALS USING FIGO CRITERIA

Cardiotocography is a biophysical method of fetal monitoring during pregnancy and labour. It is mainly based on recording and analysis of fetal heart activity. The computerized fetal monitoring systems provide the quantitative description of the recorded signals but the effective methods supporting the conclusion generation are still needed. The evaluation of the signal can be made using criteria recommended by FIGO. Nevertheless, the quantitative description of the traces is inconsistent with qualitative nature of the obstetric knowledge. Therefore, we applied the fuzzy system based on Takagi-Sugeno-Kang model to evaluate and classify signals. FIGO guidelines were used for developing a set of fuzzy conditional rules defining the system performance. The proposed system was evaluated using data collected with computerized fetal surveillance system – MONAKO. The classification results confirm the improvement of the fetal state evaluation quality while using the proposed fuzzy system support.

1. INTRODUCTION

Cardiotocography is a standard clinical technique for assessment of fetal wellbeing during pregnancy and labour. It consists in Doppler ultrasound recording of the fetal heart rate (FHR) and analysis of its relationship to fetal movements and maternal uterine contractions. Early diagnosis of fetuses at risk is of significant importance as it enables to avoid dangerous situations during pregnancy which are more difficult or even impossible to manage in the newborn. The classification of the FHR signals is based on the analysis of the baseline FHR and the heart rate variability around it. The resting level of the fetal heart rate (the baseline FHR) ranges between 110 and 150 beats per minute (bpm). Small irregularity of cardiac rhythm around the baseline shows that the central nervous system is intact and provides good adaptation abilities. Acceleration patterns, as the temporary increases of FHR in response to fetal movement, are the signs of fetal wellbeing as the symptoms of the alertness of the central nervous system. Fetal distress is usually revealed by deceleration patterns, as temporary slowing of the FHR related to dangerous oxygen deficiency.

Numerous attempts were made to formalize the criteria for signals evaluation. Nevertheless, interpretation guidelines provided by the International Federation of Obstetrics and Gynaecology (FIGO) [2] are commonly used in the clinical practice. The FIGO classification criteria for antepartum FHR are based on the assessment of the baseline as well as deceleration and acceleration patterns. However, the visual analysis of graphical patterns describing the FHR variability, directly from bedside monitor printouts, is difficult even for experienced clinicians. Moreover, the interpretation is highly subjective and dependent on the clinical expert knowledge and experience. Therefore, the computerized fetal monitoring systems providing the quantitative description of the signals are widely used and this method remains a good screening procedure due to the high efficiency in fetal well-being reassuring. Consequently, effective methods for the diagnosis support are still the topic of many studies [1], [5], [6].

The strict quantitative description of the FHR traces is inconsistent with qualitative nature of the clinical obstetric knowledge. Thus, our idea was to apply the concepts of fuzzy sets and fuzzy logic to evaluate the fetal wellbeing. The fuzzy sets and fuzzy logic [11] were used in many areas of medicine as they enable to model and deal with vague and imprecise information, such as inexact measurements or expert knowledge expressed in the form of verbal descriptions. Our fuzzy system approach is based on the Takagi-Sugeno-Kang (TSK) model [10], [11]. Due to its non-linearity and simple structure, the TSK model enables to approximate highly complex systems by means of a small number of fuzzy rules. Nevertheless, the determination of a set of fuzzy rules (the rule base) that represents the knowledge of the analyzed phenomena is the basic problem when designing fuzzy systems. In our approach the rule base was developed using the FIGO guidelines for the use of antepartum electronic fetal monitoring.

2. FIGO CRITERIA

The FIGO is the worldwide organization that represents professional societies of obstetricians and gynaecologists in over one hundred countries or territories. In 1985 the FIGO Subcommittee on Standards in Perinatal Medicine and subsequently FIGO Standing Committee on Perinatal Mortality and Morbidity provided guidelines to assist in the proper use of electronic fetal heart rate monitoring [2]. According to them, antenatal FHR patterns are divided into three classes: “normal”, “suspicious” or “pathological”, representing the fetal state. The interpretation is based on analysis of quantitative parameters describing the fetal heart rate including the baseline, acceleration and deceleration patterns and instantaneous variability.

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The baseline FHR is defined as “the mean level of the FHR when this is stable, accelerations and decelerations being absent” [2]. Acceleration and deceleration episodes represent transient deviation of the FHR around the baseline with established range of amplitude and duration. According to the FIGO definition, the acceleration is recognized if the increase in FHR above the baseline is of 15 bpm or more, and lasting 15 s or more. Deceleration is a transient episode of slowing of the fetal heart rate below the baseline level of more than 15 bpm and lasting minimum of 10 s. We considered three types of decelerations: type A (D_A) with amplitude higher than 15 bpm and duration longer than 10 s, type B (D_B) with amplitude higher than 10 bpm and lasting more than 25 s, and type C (D_C) with amplitude above 15 bpm, longer than 10 s and connected with recognized uterine contraction. The instantaneous variability refers to changes of the fetal heart rate. There are two types of FHR variability distinguished: short-term variability defining changes of intervals between two consecutive heart beats (called beat-to-beat variability), and long-term variability with periodical changes of beat-to-beat variability concerning both direction and magnitude (called oscillations of FHR). We used the STV index [10] as short-term variability one, which is the most extensively studied parameter, showing correlation with the presence of metabolic acidosis and intrauterine death. Analyzing the long term variability we distinguished four different types of oscillations: “O_0”, if the amplitude A of long-term variability is in the range $A \in [0, 5]$ bpm, “O_I” for $A \in (5, 10]$ bpm, “O_{II}” for $A \in (10, 25]$ bpm and “O_{III}” for $A>25$ bpm. The classification criteria for antepartum traces according to the FIGO presents 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 [number per hour]	> 12	(1.5, 12]	[0, 1.5]
Decelerations [number per hour]	$D_A \in [0, 1.5)$ 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 $O_I \geq 40$	$O_0 \geq 40$

As the clinician diagnosis expressed in the form of natural language statements is difficult to process with the computer algorithm, we defined the scoring system (named as “non-fuzzy” in the following considerations), consistent with FIGO guidelines. Similarly to [3] we assigned the score of 2, 1 or 0 points to parameter, which value is in the “normal”, “suspicious” or “pathological” range, respectively. For the purpose of clarity and consistency in interpretation, the total score of the signal was considered “normal” if the score was in the range: 8÷10, “suspicious” with the score: 5÷7 or “pathological” with the score ≤ 4.

Nevertheless, the strict quantitative description of the FHR traces is inconsistent with qualitative nature of obstetric knowledge. The exact limits of quantitative parameters represent the uncertain boundaries between pathological and normal fetal state. For example, the STV value equal to 6.0 ms is regarded as pathological, however the 6.1 ms already represents the fetal wellbeing. Therefore, we proposed the fuzzy scoring system based on TSK model for FHR signal evaluation.

3. FUZZY SCORING SYSTEM

Takagi-Sugeno-Kang fuzzy model generates inference results with fuzzy if-then rules. To define the fuzzy scoring system based on FIGO criteria we used single input and single output form of the rules:

$$\underset{1\leq i\leq I}{\forall} R^{(i)} : \ _{if}\left(x_0 \ \mathbf{is} \ A^{(i)}\right)_{then} \ y^{(i)} = f_i\left(x_0\right), \tag{1}$$

where: I denotes the number of rules, x_0 is the input, $A^{(i)}$ is the linguistic value of linguistic variable in the antecedent of the rule, represented by a fuzzy set with the membership function $\mu^{(i)}(x)$, $y^{(i)}$ is the rule output value and $f_i(x_0)$ is a consequent function. The overall TSK fuzzy system output is calculated as weighted average of single rules output:

$$y_0 = \frac{\sum_{i=1}^{I} \mu^{(i)}(x_0)\, y^{(i)}}{\sum_{i=1}^{I} \mu^{(i)}(x_0)}. \tag{2}$$

The equation (2) defines the TSK system as the mixture of experts (models). The output value of the system is evaluated as a linear combination of I outputs $y^{(i)}$ of local models, each represented by a single fuzzy rule. Overlapping of fuzzy sets from premises guarantees smooth switching between models. We used the TSK fuzzy model for evaluating the fetal state. The system rule base was determined using data collected with computerized fetal surveillance system and FIGO guidelines. The input linguistic variables of the system are the quantitative parameters of the FHR signal: baseline, accelerations, decelerations, STV and oscillations. The linguistic values of these variables are the ranges characterizing the normal, suspicious and pathological fetal state. The linguistic values are represented by fuzzy sets defined using the membership functions. We applied the following trapezoidal membership function:

$$\mu^{(i)}(x) = \begin{cases} 0, & x \le a, \\ \dfrac{x-a}{b-a}, & a < x \le b, \\ 1, & b < x \le c, \\ \dfrac{d-x}{d-c}, & c < x \le d, \\ 0, & d < x, \end{cases} \tag{3}$$

where *a, b, c, d* are function parameters. The exact shape of the membership function is not crucial. The most important for the accurate model of reasoning is the population data [7]. Therefore, the basic points of the membership function were acquired from statistics of the investigated database. Two substantial points *b* and *c* were determined by the lower and upper quartile for the set of values of the given quantitative parameter measures. The other two: *a* and *d* were determined to get the 0.5 value of the membership for the range limits (see Fig. 1).

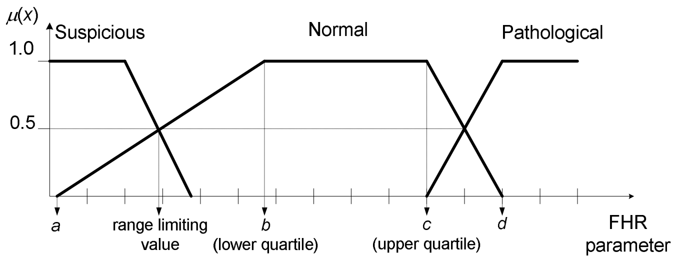

Fig. 1. The general idea of the membership function defining the "normal" range of a parameter quantitatively describing a given FHR feature.

If we denote the lower limit of the range as *l* and the upper as *u*, then the membership function parameters *a* and *b* are given as:

$$a = 2 \cdot l - b, \quad d = 2 \cdot u - c. \tag{4}$$

The resulted values of membership function parameters are shown in Table 2. An example of the membership functions referring to the FHR baseline is shown in Fig. 2.

Table 2. Parameters of the membership functions connected with particular FHR features

Parameter		**Baseline**									
range		[0,100)		[100, 110)		[110, 150]		(150, 170]		> 170	
a	b	0.00	0.00	98.5	101.5	83.43	136.57	148.07	151.93	167.86	172.14
c	d	98.08	101.92	108.26	111.74	144.77	155.23	157.89	182.11	-	-
Accelerations						**D_A**					
[0, 1.5]		(1.5, 12]		> 12		[0, 1.5)		≥ 1.5			
0.00	0.00	-1.13	4.13	10.50	13.50	0.00	0.00	1.20	1.80		
0.00	3.00	8.88	15.12	-	-	0.00	3.00	-	-		
D_B						**D_C**					
0		[0, 1.5)		≥ 1.5		0		[0, 1.5)		≥ 1.5	
0.00	0.00	0.00	0.00	1.20	1.80	0.00	0.00	0.00	0.00	1.22	1.78
0.00	0.00	0.00	3.00	-	-	0.00	0.00	0.00	3.00	-	-
STV						**O_0**					
[0, 6)		[6, 14]		> 14		0		[0, 40)		≥ 40	
0.00	0.00	5.39	6.61	8.19	19.81	0.00	0.00	0.00	0.00	38.60	41.40
5.38	6.62	8.19	19.81	0.00	0.00	0.00	0.00	7.90	72.10	-	-
O_I						**O_{III}**					
[0, 40)		≥ 40				0					
0.00	0.00	37.50	42.50			0.00	0.00				
29.40	50.60	-	-			0.00	0.00				

The rules output is defined as a score for a given range of the FHR parameter. In other words, the score determines the location of the fuzzy singleton in consequent. As a result, we got the following definition of consequent functions:

$$y^{(i)} = f_i\left(x_0\right) = p_0^{(i)}, \tag{5}$$

where $p_0^{(i)}$ is the score for the i-th range.

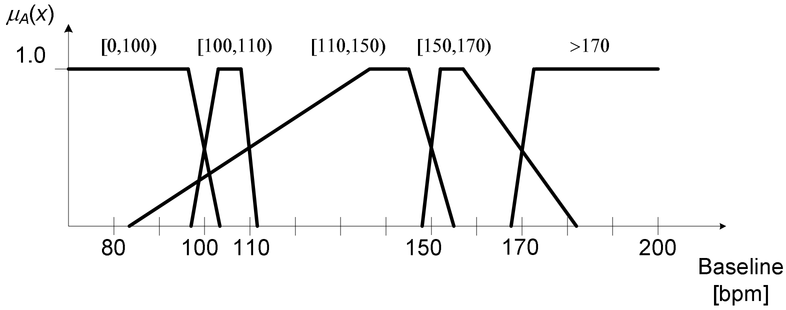

Fig. 2. Example of the membership functions calculated for the FHR baseline

We have 25 different ranges for all the analyzed FHR parameter provided by FIGO guidelines. Thus, the rule base of the fuzzy system is comprised of I = 25 fuzzy rules, one for each range. The overall output value of TSK fuzzy system (2) defines the final score for the FHR signal. The signal was considered "normal" if the fuzzy score was ≥ 7.5, "suspicious" with the score in the range [4.5, 7.5) or "pathological" with the score < 4.5.

An example of the fuzzy scoring process, determined for one input (accelerations) is shown in Fig. 3. We assumed two accelerations per hour as a result obtained from the computerized analysis. Its membership value to the range [0, 1.50] is $\mu^{(1)}(2)$=0.3333, to the range (1.5, 12] is $\mu^{(2)}(2)$=0.5951, and to the range >12 is equal to $\mu^{(3)}(2)$=0.0000. According to (2) we got the overall accelerations score y_0=0.6410. From the non-fuzzy scoring system we got the score number equal to 1. Both indicate the "suspicious" pattern of the FHR signal.

4. RESULTS

The research material used in our experiments contains the results of quantitative analysis of signals from bedside fetal monitors. The original, raw research database included 1419 records collected with computerized fetal surveillance system MONAKO [4] from 193 unselected patients of the Obstetrical Department of Medical University of Silesia in Katowice. After removing the incomplete data as well as traces recorded during labour, we obtained the database comprised of 913 antepartum records from 77 patients.

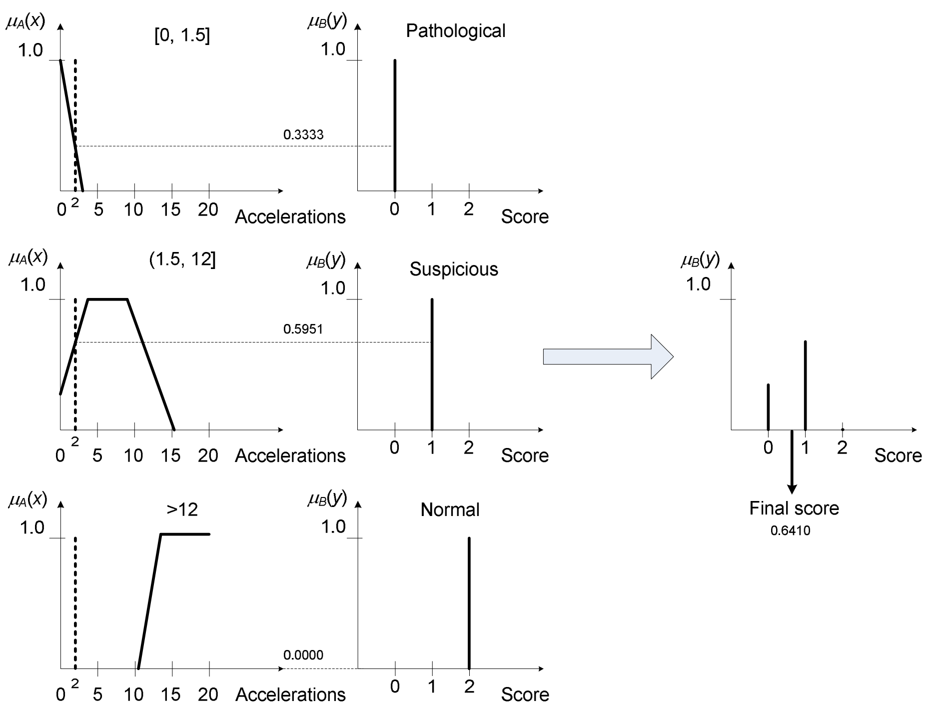

Fig. 3. Example of fuzzy rules defined for the acceleration patterns being the positive feature of the FHR trace

Taking into account the fact that with the progress of pregnancy the features characterizing the signals are changing, we decided to use only the earliest patient records (the mean gestational age was 35 weeks) to evaluate the quality of the fuzzy scoring system. As the reference we applied the non-fuzzy scoring system based on FIGO criteria. The detailed results of the classification (the confusion matrix) are shown in Table 3.

Table 3. The classification results using fuzzy and non-fuzzy scoring systems

	Fuzzy			
Non-fuzzy	Pathological	Suspicious	Normal	
Pathological	10	5	0	15
Suspicious	5	52	0	57
Normal	0	0	5	5
	15	57	5	

In five cases the fuzzy system classified the monitoring signals as “suspicious”, whereas the evaluation of non-fuzzy system was “pathological”. For the same number of cases the non-fuzzy system provided the result “suspicious”, whereas the classification result of fuzzy scoring system was “pathological”. The overall number of correct classified cases expressed as the percentage of the data set size (CC) was equal to 87.01%. To evaluate the performance indexes: sensitivity (SE), specificity (SP), positive (PPV) and negative (NPV) predictive values we applied two approaches. In the first, all the “suspicious” patterns were considered to be “pathological”, whereas in the second the “normal”. The obtained classification results are shown in Table 4.

Table 4. The performance of the proposed fuzzy scoring system

Performance index	Suspicious as pathological	Suspicious as normal
SE	100.0%	66.67%
SP	100.0%	91.94%
PPV	100.0%	66.67%
NPV	100.0%	91.94%
CC	100.0%	87.01%

In the first approach we got the same classification results for both the scoring systems. However, in the second – ten cases were misclassified. To summarize, we can get the perfect fuzzy system compatibility with non-fuzzy scoring system only when considering the “suspicious” pattern as “pathological”. We got the differences in diagnosis for ten patients when classifying the “suspicious” pattern as “normal”. For all patients, the differences in the overall score were the result of scoring the quantitative parameters having values closed to the range limits separating “suspicious” and “pathological” fetal state. The detailed results are shown in Table 5.

Table 5. The score results for fuzzy and non-fuzzy systems, for the cases diagnosed differently

Patient number	24	43	47	51	55	59	62	64	65	76
Non-Fuzzy score	4	4	5	5	4	5	4	5	5	4
Fuzzy score	4.69	4.76	4.37	4.43	4.66	4.26	5.38	4.42	4.43	4.99

The biggest difference 1.38 point was obtained for the patient number 62. When considering the quantitative data of this patient record, the biggest difference in the score was the result of STV measure that was equal to 5.981 ms. The non-fuzzy score of STV is then 0. But for the fuzzy scoring system, we could have observed that the membership value to the range [0, 6) was 0.5153 and to [6, 14) was 0.4844. Therefore, the total fuzzy score was equal to 0.9689 points. For the same reasons there were differences in the overall score for other cases. Nevertheless, the results of fuzzy scoring system are more consistent with the qualitative nature of obstetric knowledge and also human reasoning.

5. CONCLUSIONS

In the presented work, we investigated the ability of the application of the fuzzy scoring system for evaluating the fetal wellbeing. We constructed Takagi-Sugeno-Kang fuzzy model based on FIGO guidelines that were provided to assist in the proper use of electronic fetal monitoring. The parameters of the fuzzy rules were acquired from statistics of the data collected with computerized fetal surveillance system. The experiments showed high compatibility of the fuzzy with non-fuzzy scoring system. Nevertheless, the fuzzy system was more suitable for representing the uncertain boundaries between pathological and normal fetal state and providing the qualitative assessment of the FHR patterns.

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