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IMPROVING THE QUALITY OF THE FETAL STATE ASSESSMENT WITH EPSILON-INSENSITIVE LEARNING METHODS

Recording and analysis of fetal heart rate (FHR) signal is nowadays the primary method for the biophysical assessment of the fetal state. Since the correct interpretation of crucial FHR characteristics is difficult, methods of automated quantitative signal evaluation are still the subject of the research studies. In the following paper we investigated the possibility of improvement of the fetal state evaluation on the basis of the epsilon-insensitive learning (eIL). We examined two eIL procedures integrated with fuzzy clustering algorithms as well as different methods of logical interpretation of the fuzzy conditional statements. The quality of the FHR signal classification was evaluated using the data collected with the computerized fetal surveillance system. The learning performance was measured with the number of correct classification (CC) and overall quality index (QI) defined as a geometric mean of sensitivity and specificity. The obtained results (CC = 88 % and QI = 87 %) show a high efficiency of the fetal state assessment using the epsilon-insensitive learning based methods.

1. INTRODUCTION

Fetal state monitoring is an essential element of modern perinatology. Among the methods of biophysical assessment of the fetal state, the procedures of registration and analysis of fetal heart rate (FHR) are of particular importance. Normal fetal heart rate shows the adequate blood circulation and oxygenation and indicates the proper functioning of the fetal central nervous system. One of the most important methods of the FHR signal acquisition is the Doppler ultrasound method, which involves the tracking of mechanical activity of the fetal heart. The graphical representation of the signal is to be evaluated by a clinician, whose task is to identify and classify the signal patterns including the basal FHR level (the baseline) and its variability. The ability to objective evaluation of the FHR signal characteristics is essential for the correct assessment of the fetal state. However, the complexity of patterns representing the FHR variability makes the visual signal interpretation difficult [1]. The accuracy of the analysis depends mostly on clinician's psychophysical condition and experience. In order to improve the reproducibility and objectivity of the fetal state evaluation the visual assessment was replaced by automated analysis. The computerized fetal monitoring systems provide the complete quantitative description of the FHR signal however, despite the novel and

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more advanced algorithms for signal analysis [18], methods ensuring the effective support of the diagnostic process are still the aim of research.

Different procedures of automated FHR signal evaluation have been proposed so far but the computational intelligence based methods are of special interest [10], [13]. Among them the algorithms inspired by the statistical learning theory (SLT) [19] can be distinguished. One of the most representative example of the practical application of SLT are the support vectors machines (SVMs) [16]. The SVM based procedures of the qualitative assessment of the fetal state were shown in [8], [12], [5]. The applications of the neuro-fuzzy classifier which parameters were estimated with epsilon-insensitive learning [14] - another method derived from the fundamentals of the SLT were presented in [3], [4]. The solutions using epsilon-insensitive learning [3], [4] have been based so far mainly on the conjunctive interpretation of fuzzy rules combined with fuzzy c -means clustering [2]. However, the improvement of the fetal state assessment accuracy can be achieved by the application of the fuzzy modelling based on fuzzy implications (logical interpretation of fuzzy rules) [7] and the robust clustering. Hence, in the presented study we used an iterative solution of the epsilon-insensitive learning combined with fuzzy c -median clustering [11] for different methods of interpretation of the fuzzy conditional statements.

2. THE ANBLIR NEURO-FUZZY SYSTEM LEARNING

The process of FHR signal evaluation by a clinician is difficult to be represented in the algorithmic form. Also, there is no explicit method of expert knowledge acquisition. Therefore, the fuzzy systems are applied for modelling of the diagnostic scheme, which is used to assess the FHR recordings. Fuzzy inference results are given by a set of linguistic if-then statements (rule base), with premises and/or consequences defined by fuzzy sets. The Artificial Neural Network Based on Logical Interpretation of the fuzzy if-then rules (ANBLIR) [15] is an example of a neuro-fuzzy system which learning procedure is simultaneously a method of automated fuzzy conditional rules extraction from numerical data. In this study the analysed dataset consists of parameters of the quantitative description of the real FHR signals.

The conditional statement is a natural language expression:

$$\mathbf{if } A \mathbf{ then } B, \quad (1)$$

which in case of the classical logic is given by an implication $A \Rightarrow B$. However, the most common method of interpreting the fuzzy conditional statements is the conjunctive interpretation. In the conjunctive interpretation fuzzy rules are given as an intersection of premise (A) and consequent (B) fuzzy sets, defined by t -norm $\mu_A \star_t \mu_B$, where μ_A, μ_B , are the membership functions. However, the t -norm definition (e.g. the minimum or algebraic product) and hence the conjunctive interpretation remains inconsistent with the interpretation of if-then rules derived from classical logic, in which only the true antecedent can not imply false consequent. As a result, the concept of fuzzy implications $I(\mu_A, \mu_B)$ analogous to the classical logical implications was introduced [7]. The interpretation of fuzzy rules, based on fuzzy implications is referred to as a logical interpretation. In the presented work we studied five different fuzzy implications which definitions are shown in Table 1.

The ANBLIR uses a set of fuzzy conditional statements in the form:

$$\forall_{1 \leq i \leq I} R^{(i)} : \mathbf{if and} \mathop{\mathbf{and}}^t \left(x_{0j} \mathbf{ is } A_j^{(i)} \right) \mathbf{ then } Y \mathbf{ is } B^{(i)}(\mathbf{x}_0), \quad (2)$$

where I denotes the number of rules, t is the number of inputs, x_{0j} is the j -th element of the input vector $\mathbf{x}_0 = [x_{01}, x_{02}, \dots, x_{0t}]^T$, and Y is the output linguistic variable.

Table 1. Fuzzy implications

Implication	$I(\mu_A, \mu_B)$	$g(F, w)$
Gödel	$\begin{cases} 1, & \mu_A \leq \mu_B, \\ \mu_B, & \mu_A > \mu_B, \end{cases}$	$\frac{w}{2} (2 - 2F + F^2),$
Gougen	$\min\left(\frac{\mu_A}{\mu_B}, 1\right),$	$\frac{w}{2} (2 - F),$
Łukasiewicz (Mamdani)	$\min(1 - \mu_A + \mu_B, 1),$	$\frac{w}{2} F (2 - F^2),$
Reichenbach (Larsen)	$1 - \mu_A + \mu_A \mu_B,$	$\frac{w}{2} F,$
Zadeh	$\max(1 - \mu_A, \min(\mu_A, \mu_B)),$	$\begin{cases} \frac{w}{2} (2F - 1), & F \geq \frac{1}{2}, \\ 0, & F < \frac{1}{2}. \end{cases}$

The premise fuzzy sets $A_j^{(i)}$ have Gaussian membership function which is defined with a help of two parameters, the center $c_j^{(i)}$ and the dispersion $s_j^{(i)}$. The conjunction **and** of multi-input rules is represented by an algebraic product. Consequently, the firing strength (the level of activation) can be expressed as:

$$\forall_{i=1,2,\dots,I} F^{(i)}(\mathbf{x}_0) = \prod_{j=1}^t \mu_{A_j^{(i)}}(x_{0j}) = \exp \left[-\frac{1}{2} \sum_{j=1}^t \left(\frac{x_{0j} - c_j^{(i)}}{s_j^{(i)}} \right)^2 \right]. \quad (3)$$

The consequent fuzzy sets $B^{(i)}$ have triangle (isosceles triangle) membership function, defined with the width of triangle base $\mathbf{w}^{(i)}$ and the centre of gravity location being the linear combination of inputs: $y^{(i)}(\mathbf{x}_0) = \mathbf{p}^{(i)T} \mathbf{x}'_0$, where $\mathbf{x}'_0 = [1, \mathbf{x}_0]^T$, and $\mathbf{p}^{(i)} = [p_0^{(i)}, p_1^{(i)} \dots, p_t^{(i)}]$ is a vector of parameters.

The applied interpretation of the fuzzy rule defines the relation between $F^{(i)}(\mathbf{x}_0)$ and $\mathbf{w}^{(i)}$ which can be represented as a function $g(F^{(i)}(\mathbf{x}_0), w^{(i)})$ (Table 1). An important feature of the ANBLIR fuzzy inference system is the equivalence between the conjunctive interpretation of fuzzy rules using Mamdani and Larsen relations and the logical interpretation based on Łukasiewicz and Reichenbach implications respectively.

Assuming additionally the normalized arithmetic mean as an aggregation operator and the modified indexed center of gravity defuzzification [6] we can evaluate the crisp ANBLIR output:

$$y_0 = \frac{\sum_{i=1}^I g(F^{(i)}(\mathbf{x}_0), w^{(i)}) y^{(i)}(\mathbf{x}_0)}{\sum_{j=1}^I g(F^{(j)}(\mathbf{x}_0), w^{(j)})} = \sum_{i=1}^I G^{(i)}(\mathbf{x}_0) y^{(i)}(\mathbf{x}_0). \quad (4)$$

The equation (4) defines the functional equivalence between the ANBLIR fuzzy system and normalized radial basis function neural network. Consequently, the unknown parameters of fuzzy rules can be calculated using the learning algorithms of artificial neural networks. For further considerations, we assume the training set that includes N pairs: an input vector $\mathbf{x}_0(n) \in \mathbb{R}^t$ and the desired output value $t_0(n) \in \mathbb{R}$. The input vector consists of the parameters of the quantitative description of the FHR signals and the output value represents the fetal state, $t_0(n) = -1$ for the fetal well-being or $t_0(n) = +1$ in case of pathology. Hence, the FHR signal is assumed as pathological if $y_0(\mathbf{x}_0) > 0$ or normal if $y_0(\mathbf{x}_0) \leq 0$. The task is to extract the rule base that allow for the best classification of the FHR signals.

To find the unknown membership function parameters of premise fuzzy sets $c_j^{(i)}$, $s_j^{(i)}$ we applied fuzzy clustering. Clustering is an unsupervised learning method which divides a set of objects into groups (clusters, categories, subsets), whose elements are characterized by a certain similarity. The criteria for determining the level of similarity are usually defined on the basis

of selected characteristics of the object that is represented numerically by a so-called feature vector. Many clustering algorithms have been defined as multi-criteria optimization problems, based on the minimization of a scalar criterion. Fuzzy methods, which assume the possibility of partial membership of the object in the formed groups can be distinguish among them. In the present approach, we used two algorithms for fuzzy c -means (FCM) [2] and fuzzy c -medians (FCMed) [11]. Our feature vector is defined as a set of parameters of quantitative description of the fetal heart rate signal \mathbf{x}_0 . These features are divided into a given number of groups c , which corresponds to the number of fuzzy rules to be extracted $c = I$. Each group is represented by the so-called prototype \mathbf{v}_i ($\forall i = 1, 2, \dots, I$), which is defined as the weighted average of the group elements:

$$\forall_{1 \leq i \leq I} \mathbf{v}_i = \frac{\sum_{n=1}^N (u_{in})^2 \mathbf{x}_0(n)}{\sum_{n=1}^N (u_{in})^2}, \quad (5)$$

where $u_{in} \in [0, 1]$ is the element of the partition matrix \mathbf{U} , defining the degree to which the object belongs to groups ($u_{in} = 1$ defines full membership).

The FCM creates a partition based on the minimal Euclidean distance between objects and group prototypes. Consequently, the FCM prototypes are linear statistics of data, which is vulnerable to outliers [11]. Therefore, in the study on the possibility of improvement of the fetal state assessment we used the robust median fuzzy clustering (FCMed) as well. In FCMed, cluster prototypes are the fuzzy (weighed) medians with weights $(u_{in})^2$ defined as:

$$\forall_{1 \leq i \leq I} \forall_{1 \leq n \leq N} u_{in} = \frac{(1/d_{in})^2}{\sum_{j=1}^I (1/d_{jn})^2}, \quad (6)$$

where $d_{in} = \|\mathbf{v}_i - \mathbf{x}_0(n)\|_1 = \sum_{j=1}^t |v_{ij} - x_{0j}(n)|$ is the ℓ_1 metric.

The classical algorithm of the fuzzy median calculation requires ordering the feature vector elements. Hence, to increase the computational efficiency we used the procedure [11] of the fuzzy median calculation based on the bisection method. The final FCMed partition is determined from (5) and (6) with the the random partition matrix as the starting point. The clustering results \mathbf{U} and \mathbf{v}_i are used to calculate the parameters of the ANBLIR fuzzy rules according to the following equations:

$$\forall_{1 \leq i \leq I} \forall_{1 \leq j \leq t} c_j^{(i)} = \frac{\sum_{n=1}^N (u_{in})^2 \mathbf{x}_{0j}(n)}{\sum_{n=1}^N (u_{in})^2}, \quad (7)$$

$$\forall_{1 \leq i \leq I} \forall_{1 \leq j \leq t} \left(s_j^{(i)} \right)^2 = \frac{\sum_{n=1}^N (u_{in})^2 \left(\mathbf{x}_{0j}(n) - c_j^{(i)} \right)^2}{\sum_{n=1}^N (u_{in})^2}. \quad (8)$$

In the original learning procedure of ANBLIR, the parameters $\mathbf{p}^{(i)}$ of the linear equation in the rules consequent are determined by the least squares method, assuming the cost function in the form of mean square error. Consequently, only the full correspondence between the fuzzy model and the modelled process leads to the zero loss (zero error). A different approach presents epsilon-insensitive learning (eIL), which mimics the human reasoning in terms of high tolerance for imprecision. In eIL, the limiting value of tolerance is denoted as ε and the zero loss is obtained if the absolute error is less than ε :

$$E_n = |t_0(n) - y_0(n)|_{\varepsilon} = \begin{cases} 0, & |t_0(n) - y_0(n)| \leq \varepsilon, \\ |t_0(n) - y_0(n)| - \varepsilon, & |t_0(n) - y_0(n)| > \varepsilon. \end{cases} \quad (9)$$

The optimization methods based on the above definition are called the epsilon-insensitive learning. They lead to the increase of the solution quality in terms of improving the generalization ability and robustness to outliers.

The process of determining the parameters $\mathbf{p}^{(i)}$ on the basis of the the epsilon-insensitive learning can be formulated as the minimization problem subject to constraints related to local or global solution. In the global approach, the rules parameters are defined as a single task of epsilon-insensitive learning, while in the local approach, the solution is obtained as the result of I independent weighted eIL problems. Both require the quadratic programming (QP) which, in its classical form, is the method of very high computational complexity. However, in the literature [14] more efficient solutions of the QP were shown. In our study we applied the algorithm of iterative quadratic programming (IQP) for both the global IQP_g as well as the local IQP_l approach.

The another unknown parameter of the consequent membership function is the width of the triangle base. In the presented approach we assume $w^{(i)} = 2, 1 \leq i \leq I$.

3. RESEARCH MATERIAL

The research material used in our experiments is the collection of the FHR signals from the one-hour fetal monitoring sessions. The dataset consists of parameters of the quantitative description of the FHR signals and the corresponding newborn outcome attributes obtained from newborn forms. The signals were recorded using HP 50 series monitor from the patient abdomen via external pulsed Doppler ultrasound transducer. The raw research material was analysed in order to eliminate the incomplete data (with missing values of the newborn attributes). We excluded also the recordings characterized by a high signal loss ($> 20\%$). Finally we obtained a set of 180 antenatal recordings with the mean gestational age of 33 weeks, which were derived from 50 patients. As fuzzy system inputs we used the parameters of the quantitative description of FHR signal, which according to the FIGO criteria [17] are essential when assessing the fetal state. Consequently, we evaluated $t = 9$ parameters: the mean baseline value bFHR [bpm], the number of identified acceleration patterns ACC [1/h] [5], the number of identified deceleration patterns of three types [5]: DEC_A [1/h], DEC_B [1/h] and DEC_C [1/h], the short-term variability STV [ms], and the long-term variability expressed as oscillation of three types [9]: OSC₀, OSC_I and OSC_{III}.

Qualitative assessment of FHR signal consists in assigning it to one of two classes, defining the fetal state as normal or pathological. As there is no other noninvasive diagnostic method that could serve as reference, the result of the signal analysis can not be verified during pregnancy. The actual fetal state can be assessed only after delivery. However, in perinatology it is assumed that during the course of pregnancy the fetal state can not change rapidly. Hence, the newborn outcome can be retrospectively related to the fetal state at the time of FHR signal acquisition. Consequently, the results of qualitative assessment of the fetal state can be considered as the prediction of newborn outcome.

The newborn outcome can be evaluated on the basis of the analysis of delivery attributes. There are three main attributes that are used in practice: fetal birth weight, Apgar score and the pH measurement in the blood from the umbilical vein. Among them, the most objective indicator of newborn pathology is the pH level. Therefore, in the presented study the pH level is assumed as a reference. Thus, results of the FHR signal analysis correspond to the assessment of the fetal acidosis, being the symptom of fetal hypoxia. The values of $\text{pH} \geq 7.20$ indicate the newborn well-being, while $\text{pH} < 7.10$ the newborn pathology.

The risk of hypoxia was detected in 6 fetuses from which the total number of 34 recordings were acquired (19% of the whole dataset). We founded two patients (8 recordings) with the pH in the range $\text{pH} \in [7.10, 7.20)$. They are usually excluded from the analysis [8], however, due to high percentile of the birth weight and high Apgar score both were assigned to the class of the fetal well-being.

4. RESULTS AND DISCUSSION

The result of fuzzy analysis of the FHR signal is the assessment of the fetal state. The accuracy of the evaluation was determined on the basis of the confusion matrix. In addition to the number of correct classifications (CC), defined as the number of correctly classified cases, expressed as the percentage of the of testing set size, we determined the sensitivity (SE) and specificity (SP). However, the evaluation of the classification performance is difficult when analysing all the prognostic indices simultaneously. Hence, we used also the overall quality index $QI = \sqrt{SE \cdot SP}$.

The learning was performed for 50 random divisions of the whole dataset into two equal parts: learning and testing. The classifiers settings were determined using the algorithm specification leading to the maximum QI calculated for the 10 first divisions. The results presented in the tables represent the mean values determined for all 50 divisions. The evaluation of the fetal state using epsilon-insensitive learning was carried out for all considered fuzzy implications (Table 1) with the number of fuzzy rules I changed from 2 to 6. The eIL parameters ε and τ , as well as the parameters γ and σ for the reference LSVM procedure [16] were selected from the range $[10^{-3}, \dots, 10^3]$ with steps $\{10^{-3}, 10^{-2}, \dots, 10^2\}$ changed every decade. For IQP procedure $\rho = 0.98$ was assumed. The stop conditions for the learning algorithm were the execution of 1000 iterations or $\|\mathbf{p}(k-1) - \mathbf{p}(k)\| \leq 10^{-5}$. The fuzzy clustering was stopped if maximum number of 500 iterations were executed or if $\|\mathbf{U}(k-1) - \mathbf{U}(k)\| \leq 10^{-5}$. Since both, FCM and FCMed, may trap in the local minimum of criterion function J , the calculations were repeated 50 times for different random realizations of the initial partition matrix. As a result the partition characterized with the lowest value of J was selected.

Table 2 shows the best results of the FHR signals classification with eIL and FCM methods. It was noticed, that most of methods of fuzzy rules representations, including the conjunctive interpretation of the rules, did not allow to obtain the satisfactory quality of the fetal state evaluation. The exception was the Zadeh implication that improved the results of local IQP learning (QI = 85.56 %) in comparison to the reference LSVM (QI = 76.79 %). One can notice, that for the eIL learning integrated with FCM clustering, the selection of the proper method of the fuzzy conditional statements interpretation has a significant influence on the quality of the fetal state assessment.

Table 2. The best results of FHR recordings classification using eIL + FCM

	IQP _g	IQP _t	LSVM
	$I = 2$	$I = 5$	
	$\varepsilon = 0.001, \tau = 0.009$	$\varepsilon = 0.050, \tau = 0.900$	$\gamma = 4.00, \sigma = 3.00$
	Gödel implication	Zadeh implication	
QI	45.44 ± 45.05 ^{*)}	85.65 ± 5.200	76.79 ± 5.756
CC	45.99 ± 45.45	86.67 ± 1.891	87.38 ± 2.635

^{*)}mean value ± standard deviation

A significant improvement in the quality and accuracy of the FHR signals analysis was noticed when applying the FCMed clustering (Tables 3 and 4). In this case, all the considered fuzzy implications provided higher quality of the fetal state assessment than the reference LSVM (Table 2). After integrating the FCMed procedure with the local eIL learning we noticed also the decreased dependence of the method of interpretation on the classification results. However, still the appropriate fuzzy rules definition increases the quality of the fetal hypoxia prediction.

The best results (QI = 87.18%) were obtained for the Gödel implication and global IQP.

Table 3. The results of FHR recordings classification using eIL + FCMed for different fuzzy implications

	Gödel	Gougen	Łukasiewicz	Reichenbach	Zadeh
IQP _g					
	<i>I</i> = 2	<i>I</i> = 2	<i>I</i> = 2	<i>I</i> = 2	<i>I</i> = 3
QI	87.18	86.71	85.35	85.13	44.07
CC	88.11	87.87	87.00	86.91	45.51
IQP _l					
	<i>I</i> = 2	<i>I</i> = 2	<i>I</i> = 5	<i>I</i> = 6	<i>I</i> = 3
QI	85.65	85.65	84.79	85.15	85.56
CC	86.64	86.64	88.64	88.89	86.73

(Table 4). Slightly worse classification quality (QI = 85.65 %) with the Gödel definition was obtained for the local IQP. For the global learning, only the interpretation of fuzzy rules proposed by Zadeh did not allow for satisfactory fetal state assessment. It provided the solution with the overall quality index QI = 44.07 %. However, for the IQP_l combined with Zadeh implication a significant increase of QI (QI = 85.56 %) was noticed.

Table 4. The best results of FHR recordings classification using eIL + FCMed

	IQP _g	IQP _l
	<i>I</i> = 2	<i>I</i> = 2
	$\varepsilon = 0.008, \tau = 0.007$	$\varepsilon = 0.050, \tau = 0.004$
	Gödel implication	Gödel implication
QI	87.18 ± 5.102 ^{*)}	85.65 ± 5.473
CC	88.11 ± 2.552	86.64 ± 1.976

^{*)}mean value ± standard deviation

The classification quality varies with the number of extracted fuzzy rules (Tabela 5). The largest fuzzy rule base leads to the low generalization ability, which is characterized by high learning quality for the training set (being the result of perfect matching the classifier parameters to the training data) and the decreased performance of the testing data evaluation. Usually, the best results of FHR signals analysis were obtained for the fuzzy models with the smallest number of rules *I* = 2. Even if the best efficiency of learning was noted for the higher *I* (e.g. Zadeh implication, IQP_l+FCM, *I* = 5, QI = 85.65 %, CC = 86.67%), a rule base consisted of two conditional statement allowed for very similar fetal state assessment quality (QI = 85.65 %, CC = 86.64 %).

Table 5. The change of the classification performance with the change of the number of fuzzy rules using IQP_g + FCMed for Gödel implication

	<i>I</i> = 2	<i>I</i> = 3	<i>I</i> = 4	<i>I</i> = 5	<i>I</i> = 6
QI	87.18 ± 5.102 ^{*)}	78.41 ± 26.76	74.74 ± 30.82	54.12 ± 42.94	44.48 ± 44.11
CC	88.11 ± 2.552	79.33 ± 26.81	76.11 ± 31.09	55.84 ± 44.19	45.51 ± 45.05

^{*)}mean value ± standard deviation

5. CONCLUSIONS

In the presented work we investigated the possibility of improving the fetal state evaluation on the basis of the fetal heart rate signal analysis using the epsilon-insensitive learning. The quality of the FHR signal classification was verified on the basis of the newborn outcome assessment using pH measurements in the blood from the umbilical vein. We investigated local and global procedures of eIL iterative quadratic programming, integrated with fuzzy clustering algorithms (fuzzy c -means and fuzzy c -medians) for different interpretations of the fuzzy conditional statements. Our experiments shown that the selection of the appropriate interpretation of fuzzy rules is crucial for the correct assessment of the fetal state. The application of the robust FCMed clustering allowed us also to increase the learning quality for all considered fuzzy implications. The improvement was noticed in the whole considered range of the number of the fuzzy rules to be extracted, however, the highest efficiency of the fetal state assessment was noticed for the smallest rule bases. The epsilon-insensitive learning is characterized with better prediction quality of the fetal state in comparison to the reference Lagrangian support vector machine (LSVM). However, the eIL requires more parameters to be adjusted, including the selection of the most efficient interpretation of the fuzzy conditional statements.

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