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FETAL STATE EVALUATION WITH FUZZY ANALYSIS OF NEWBORN ATTRIBUTES USING CUDA ARCHITECTURE

Cardiotocography is a biophysical method of fetal state evaluation involving the recording and analysis of the fetal heart rate (FHR). Since a proper interpretation of the signal is relatively difficult, an automatic classification is often based on computational intelligence methods. The quality of classifiers based on supervised learning algorithms depends on a proper selection of learning data. In case of the fetal state evaluation, the learning is usually based on a set of quantitative parameters of FHR signal and the corresponding reference information determined on the basis of the retrospective analysis of newborn attributes. Values of the single attribute have been used so far as a reference. As a result, a part of information on the actual neonatal outcome has always been lost. The following paper presents a method of the fuzzy reasoning leading to an evaluation of neonatal outcome as a function of three newborn attributes. The fuzzy system was used in the process of a qualitative evaluation of the fetal state based on quantitative analysis of FHR signal using a support vector machine (SVM). In order to improve computational effectiveness, the learning algorithm was implemented in Compute Unified Device Architecture (CUDA). The results of these studies confirm the effectiveness of the proposed method and indicate the possibility of practical usage of the fuzzy system in supervised learning algorithms for the qualitative evaluation of the fetal state.

1. INTRODUCTION

Cardiotocography is a biophysical method of fetal monitoring based on analysis of fetal heart rate (FHR) signal registered with the ultrasonic Doppler technique. Modern methods of computer analysis of the FHR signal provide a wide range of parameters of quantitative description which help to improve the effectiveness of fetal distress detection. Unfortunately, in the process of medical diagnostics, it is difficult to transform such information into practical knowledge. Since the implementation of the heuristic rules of diagnosis used by an experienced clinician is quite complex the computational intelligence methods are used more often. The most popular procedures include the methods based on fuzzy logic [11], [17], artificial neural networks [8], [12], [16], neuro-fuzzy systems [4], [5], evolutionary optimization [9] as well as algorithms originating from the statistical learning theory [7], [6], [10], [14]. A proper selection of learning data plays a key role in an effective qualitative evaluation of the fetal state with supervised learning. In case of the fetal state evaluation, the learning is usually based on a set of quantitative parameters of FHR signal [2] and corresponding reference information about the fetal state. However, during the pregnancy period i.e. when FHR signal is registered it is impossible to obtain reliable information on the actual fetal state. Therefore some solutions [14], [17] make use of the results of an

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interpretation of a given signal received from a clinical expert. An objective prognostic value of the FHR signal analysis may be verified after delivery only. In this case, diagnosis involves a retrospective assignment of neonatal outcome to fetal state at the time of monitoring. Such verification is possible, because in perinatology it is assumed that the fetal state can not change rapidly during the course of pregnancy. Consequently, the qualitative fetal assessment may be also considered as the prediction of the neonatal outcome.

The fetal state is determined through assessment of the newborn attributes. The single attribute value [5], [7], [6], [8], [10], [12], or the output of logical function constituted by several selected attributes [4], [12] can be used in the process of learning. These solutions, however, do not use full information on the neonatal outcome which is available thanks to a simultaneous analysis of distinguished newborn attributes. For this reason, the following paper presents a fuzzy reasoning system for retrospective evaluation of the fetal state as a function of neonatal outcome attributes. The results of the fuzzy analysis were used to construct training sets for fetal state assessment using a support vector machine (SVM). In practice, the learning speed of a classifier plays a crucial role. Therefore, a modified learning algorithm based on an iterative solution LSVM (Lagrangian Support Vector Machines) was used. The LSVM procedure is characterized by higher computational efficiency than classical SVM, whereas its classification results are more accurate. Additionally, the LSVM algorithm was written in the form which made it possible to speed up the computations by applying the Compute Unified Device Architecture (CUDA).

2. EVALUATION OF NEWBORN ATTRIBUTES

A neonatal outcome is evaluated with a help of newborn attributes [3]. Three main attributes subjected to a clinical evaluation can be distinguished. These include: birth weight, determined in relation to a given population of infants and expressed in percentiles, the Apgar score which is a method of visual assessment of selected newborn features, and the acid-alkaline balance of the newborn's blood estimated by a value of negative logarithm of the hydrogen ion activity (pH) in the umbilical cord blood. For each of these attributes, certain ranges indicating a normal, suspicious, or pathological neonatal outcome are given (Table 1).

Table 1. The classification of newborn attributes.

Newborn attribute	Neonatal outcome		
	Pathological	Suspicious	Normal
Birth weight	< 5	$[5, 10)$	≥ 10
Apgar score	< 5	$[5, 6]$	≥ 7
pH	< 7.1	$[7.1, 7.2)$	≥ 7.2

A retrospective evaluation of a fetal state allows us to use a value of the single attribute, or to determine a neonatal outcome as a logical function whose arguments are the assessments of selected attributes. In this case, however, a part of information on actual neonatal outcome, which may be obtained as a result of a simultaneous analysis of selected attributes, is lost. In this paper, a simple system of fuzzy reasoning is proposed. It allows a newborn state to be assessed as a degree of membership to a fuzzy set defining a given class of neonatal outcome evaluation.

2.1. FUZZY EVALUATION OF NEONATAL OUTCOME

The fuzzy evaluation of the neonatal outcome is determined on the basis of a set of MISO (multiple input single output) fuzzy rules with inputs, constituting the values of newborn attributes, and the output, representing a neonatal outcome:

$$\underset{1 \le i \le I}{\forall} R^{(i)} : \textbf{if } \left(X_1 \textbf{ is } A_1^{(i)}\right) \textbf{ and } \left(X_2 \textbf{ is } A_2^{(i)}\right) \textbf{ and } \left(X_3 \textbf{ is } A_3^{(i)}\right) \textbf{ then } Y \textbf{ is } B^{(i)}, \tag{1}$$

where X_1 is the input linguistic variable defining the percentile of the birth weight, X_2 is the linguistic variable related to Apgar score, X_3 is the linguistic variable defining pH measurement, $A_1^{(i)}$, $A_2^{(i)}$ and $A_3^{(i)}$ are the linguistic values (terms) represented by fuzzy sets that are characterized by trapezoid membership functions $\mu_{A_j}^{(i)}(x)$, which define a class of neonatal outcome being the result of the assessment of a single newborn attribute as normal (N), suspicious (S) or pathological (P). Figure 1 illustrates an example of trapezoid input fuzzy sets defined for the hydrogen ion activity.

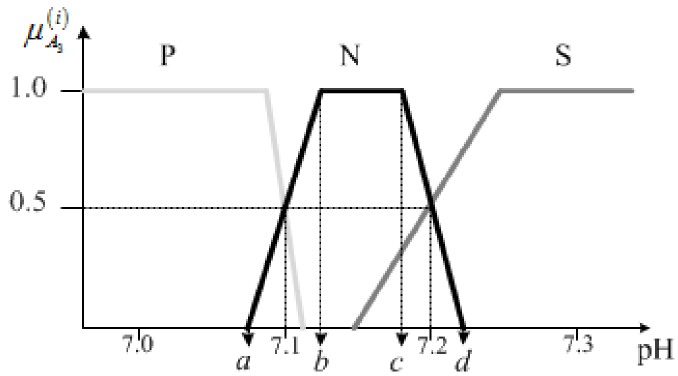

Fig. 1. An example of trapezoid input fuzzy sets defined for the hydrogen ion activity (pH) (N - denotes normal, S - suspicious, and P - pathological neonatal outcome).

The form of trapezoid input fuzzy sets is defined by means of four parameters referred to as a, b, c and d. Their values are determined by analyzing statistically an available set of newborn attributes [6].

The symbol Y (1) refers to an output linguistic variable, defining the neonatal outcome being the result of newborn attributes analysis. Fuzzy set $B^{(i)}$ represents the output linguistic value being a formulation of a natural language, describing the class of a neonatal outcome evaluation (N, S, or P), which is defined by means of triangular membership functions of output fuzzy sets $\mu_{B^{(i)}}(y)$ whose base width is equal to $w^{(i)} = 2$. Figure 2 shows an example of the triangular membership function of output fuzzy sets.

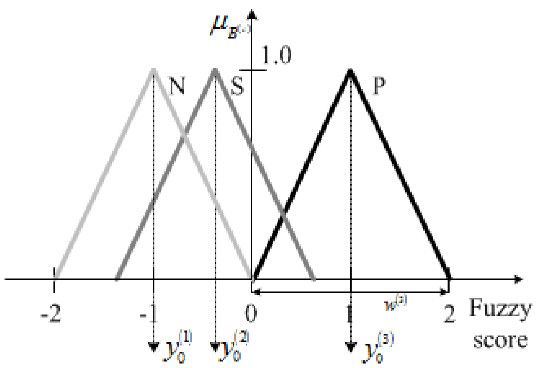

Fig. 2. An example of triangular membership function of output fuzzy sets (N - denotes normal, S - suspicious, and P - pathological neonatal outcome).

A complete rule base (1) of a fuzzy reasoning system with three inputs in which each input is represented by the linguistic variable with three linguistic values consists of $I = 3^3 = 27$ conditional statements. The inference results strictly depend on the form of the rules that defines the relationship between single newborn attributes and the final neonatal outcome evaluation. In the proposed solution, a neonatal outcome is described as:

– pathological, if any of attributes indicates the fetal pathology,

– normal, if two or more attributes indicate the fetal wellbeing,
– suspicious, for all the remaining cases.

The fuzzy system is based on Larsen's fuzzy reasoning scheme. The operator **and** (1) of antecedents of fuzzy rules is defined as an algebraic product of membership functions of input fuzzy sets $A_j^{(i)}$. Hence, the firing strength of the rules is determined as:

$$\underset{1\le i\le I}{\forall} F^{(i)}\left(\mathbf{x}_0\right)=\prod_{j=1}^{3}\mu_{A_j}^{(i)}\left(x_{0j}\right), \tag{2}$$

where $\mathbf{x}_0=\left[x_{01},x_{02},x_{03}\right]^T$ is a vector of newborn attributes.

The fuzzy rules are defined on the basis of the conjunctive interpretation with Larsen's relation:

$$\mu_{B^{(i)\prime}}\left(y\right)=\mu_{B^{(i)}}\left(y\right)\cdot F^{(i)}\left(\mathbf{x}_0\right), \tag{3}$$

where $\mu_{B^{(i)\prime}}\left(y\right)$ is the consequent fuzzy set obtained as a result of reasoning based on a single fuzzy rule. The arithmetic mean is used as an aggregation operator of the results of inference from single rules. Hence, a membership function of the output fuzzy set B' (the final conclusion) is defined as:

$$\mu_{B'}\left(y\right)=\frac{1}{I}\sum_{i=1}^{I}\mu_{B^{(i)\prime}}\left(y\right). \tag{4}$$

A crisp output value is determined in the process of defuzzification. In the proposed solution, it was assumed that representative element of the resulting fuzzy set would be determined on the basis of the location of the centre of gravity of its membership function:

$$y_0=\frac{\int y\,\mu_{B'}\left(y\right)dy}{\int \mu_{B'}\left(y\right)dy}. \tag{5}$$

On the basis of the adopted assumption concerning the form of the membership functions of output fuzzy sets (an isosceles triangle whose base width is 2), the crisp output value is given as:

$$y_0=\frac{\sum_{i=1}^{I}F^{(i)}\left(\mathbf{x}_0\right)y_0^{(i)}}{\sum_{i=1}^{I}F^{(i)}\left(\mathbf{x}_0\right)}, \tag{6}$$

where $y_0^{(i)}$ refers to the centre of gravity location of a triangle membership function of the i-th rule. Hence, the output of the fuzzy system is the weighted mean of single fuzzy rules outputs.

The location of the centers of gravity is determined by assuming that a normal neonatal outcome corresponds to negative $y_0^{(i)}=-1$, whereas the pathology to positive output value of a single fuzzy rule. To classify neonatal outcome as suspicious, a varying location of the centre of gravity $y_0^{(i)}=p^{(i)}$ is assumed, allowing for a different interpretation of newborn attributes in the ranges corresponding to the śuspiciouśclass. For $p^{(i)}>0$ the values of attributes from the ranges described as suspicious increase, whereas for $p^{(i)}<0$ the possibility of the final neonatal outcome assessment as pathological decreases. For $p^{(i)}=0$, the rule indicating a suspicious neonatal outcome does not influence the inference result.

As a final conclusion, only two classes of the newborn state assessment i.e. normal and pathological are assumed. Consequently, a neonatal outcome is classified as pathological if the positive strict output value of the fuzzy system exceeds a predefined threshold (Δ). A binary classification does not limit our considerations as it is still possible to recognize suspicious state as corresponding to $|y_0|<\Delta$.

2.2. CLASSIFICATION OF FHR SIGNAL

For a qualitative evaluation of fetal state based on an analysis of the quantitative parameters of FHR signal, a support vector machine (SVM) was used. This particular procedure originating from the statistical learning theory [19] has been widely applied in classification [1] because of its effectiveness and high generalization capability. Positive aspects of the SVM method have been also used in medical application [6], [14].

The SVM algorithm looks for an optimal hyperplane in multidimensional feature space which distinguishes between given classes with the highest margin (separation). Data (input vectors) determining this margin are called the support vectors. Since a linear classification is usually not sufficient [18], input data are transformed into a higher dimension of feature space using so-called kernel function. In this paper, the fetal state was evaluated on a basis of kernel functions in a radial form [6]. In practice, the learning speed of classifier plays a key role. For this reason, a modified algorithm of support vectors, i.e. LSVM (Lagrangian Support Vector Machines) [15] was used. In LSVM method the quadratic programming was replaced with iterative solution resulting in lower computational complexity and higher classification accuracy. Additionally, to speed up the calculations, the LSVM algorithm was implemented in the form which made it possible to apply Compute Unified Device Architecture (CUDA). All calculations were carried out in Matlab® environment.

3. RESEARCH MATERIAL

Sets of nine parameters of quantitative description of FHR signals [6] obtained from the archives of computerized fetal surveillance system [13] and corresponding newborn attribute values from neonatal forms were used as a research material. The analyzed dataset consisted of 180 recordings obtained from 50 patients. Table 2 presents the number of newborn attributes related to the distinguished classes of neonatal outcome. There were no recordings related to the pathological birth weight in the considered data.

Table 2. The number of newborn attributes related to different classes of neonatal outcome.

Newborn attribute	Neonatal outcome		
	Pathological	Suspicious	Normal
Birth weight	$0/0^{*}$	$6/9$	$44/171$
Apgar score	$2/3$	$11/47$	$37/130$
pH	$6/34$	$2/8$	$42/138$

*number of patients / number of recordings

4. RESULTS AND DISCUSSION

4.1. VALIDATION OF FUZZY EVALUATION

The quality of the fuzzy analysis was verified by comparing the inference results with the assessment of neonatal outcome using each single newborn attribute. Consequently, two solutions were used. In the first, we assigned the attributes relating to the suspicious class of neonatal outcome as representing the normal neonatal state (SaN –optimistic interpretation), whereas in the second, as the neonatal pathology (SaP – pessimistic interpretation). The quality of the evaluation was assessed on the basis of confusion matrices with a help of classical prognostic indices such as the percentage of correct classifications (CC), sensitivity (SE), and specificity (SP). To make the assessment of the classifier easier we introduced the classification quality index (QI) defined as $\mathrm{QI} = \sqrt{\mathrm{SE} \cdot \mathrm{SP}}$. A fuzzy evaluation of neonatal outcome was determined for variable $p^{(i)}$ and Δ. Values of $p^{(i)}$ were changed in the range of $[-0.75, +0.75]$, whereas values of Δ in the range of $[-0.50, +0.50]$, both with step 0.25.

Table 3 shows the best results of the fuzzy evaluation. The SaN analysis of the percentile of the birth weight was not possible due to the lack of pathological cases in the considered dataset. The highest quality of the fuzzy analysis in relation to both considered newborn attributes was obtained with the threshold $\Delta = 0.25$ and interpretation of the suspicious neonatal outcome as indicating the normal state of the newborn $p^{(i)} = -0.75$. As for the Apgar score, slightly better results (QI = 94.65) were obtained for $\left(\Delta = 0.50, p^{(i)} = -0.75\right)$.

Table 3. The results of fuzzy analysis using different interpretations of single newborn attributes.

Newborn attribute	QI	SE	SP	CC
SaN				
Apgar score	93.54	100.0	87.50	88.00
pH	97.70	100.0	95.45	96.00
SaP				
Birth weight	77.85	83.33	72.73	74.00
Apgar score	94.44	100.0	89.19	92.00
pH	88.64	100.0	78.57	82.00

In case of the SaP interpretation, the best results of the fuzzy assessment in relation to all considered newborn attributes were obtained for $\left(\Delta = 0.25, p^{(i)} = 0.75\right)$. Similarly to SaN, the applied scoring for suspicious cases remains compliant with the interpretation used for the purpose of the reference. When considering single attributes, slightly better results in case of the Apgar score (QI = 98.64) were obtained for $\left(\Delta = 0.25, p^{(i)} = 0.50\right)$, whereas in case of the birth weight (QI = 84.83) for $\left(\Delta = 0.00, p^{(i)} = -0.25\right)$.

The study results confirm that the fuzzy inference parameters may be selected in such a way that the resulting neonatal outcome evaluation remains compliant with both SaN and SaP approaches. Different solutions are obtained with variable $p^{(i)}$ scoring, that is related to the newborn attributes indicating the suspicious neonatal outcome.

The output of the fuzzy system (6) may be interpreted as a degree of certainty that one possesses in relation to a retrospective fetal state evaluation based on newborn attributes analysis. This particular piece of information may be used when constructing learning sets for the LSVM classifier. Consequently, an additional parameter (λ) defining the threshold for the final fuzzy output was introduced in the LSVM learning. The recording characterized by low value of fuzzy output ($|y_0| < \Delta$) was classified as belonging to a learning set only if the result of its fuzzy evaluation exceeded the assumed threshold ($|y_0| > \lambda$). In this way, only those recordings whose degree of certainty of the neonatal outcome evaluation was higher than λ were used in the learning of the LSVM classifier.

4.2. SUPERVISED LEARNING WITH FUZZY EVALUATION OF NEONATAL OUTCOME

The quality of the fetal state assessment using the LSVM classifier was evaluated by analyzing the prognostic indicators (CC, SE, SP, and QI) calculated as the mean for 50 random divisions of the whole dataset into two equal parts: learning and testing. Parameters leading to the best sensitivity of classification were determined on the basis of 10 first divisions. The regularization factor γ and the parameter σ of a radial kernel [6] were selected from the range of $[10^{-2}, 10^{-1}, \ldots, 10^{4}]$ with steps $\{10^{-2}, 10^{-1}, \ldots, 10^{3}\}$ changed every decade. The threshold value of the degree of certainty was changed in the range $[0.0, 0.5]$ with a step of 0.1. The results of the classification based on the fuzzy evaluation of neonatal outcome were validated by using the testing sets in which the reference fetal state was evaluated using the fuzzy system or single newborn attributes.

At the first stage, single newborn attributes were applied as a reference for fetal state evaluation in the learning and testing of the LSVM classifier. As for the Apgar score (SaN) and the percentile of birth weight (SaP), no pathological cases were recognized (QI = SE = 0.00), and all recordings were classified as indicating normal fetal state (Table 4).

A significant difference in the number of recordings indicating the pathological and normal fetal state was the reason for such poor quality of the classification. It is typical feature of the collection of the

Table 4. The results of FHR recordings classification using LSVM method with the reference fetal state evaluated on the basis of the single newborn attributes.

Reference fetal state	γ	σ	CC	QI
SaN				
Apgar score	0.01	0.01	97.78	0.000
pH	3.00	0.40	89.62	78.61
SaP				
Birth weight	0.01	0.01	94.44	0.000
Apgar score	7.00	0.30	80.49	67.21
pH	3.00	0.40	84.62	70.10

real FHR recordings, which inhibits obtaining satisfactory quality of an automatic fetal state evaluation in spite of using advanced classification methods.

Considerably better results were noticed for the LSVM classification using the fuzzy reference. Table 5 presents the classification results with LSVM learning based on the data with the highest degree of certainty (the fuzzy score exceeding the assumed threshold λ) which was tested using the single newborn attributes. The best results were obtained for the LSVM classification with both learning, as well as testing phase based on the fuzzy evaluation of the reference fetal state (last row of Table 5). It may be noted that the application of the fuzzy assessment results in increased sensitivity, and consequently higher quality of classification. This increase is however associated with relatively lower decrease in the total number of correct classifications, which results in a decrease of specificity. The relation between the quality and the accuracy of the classification can be adjusted by appropriate selection of the learning parameters. For the other sets of ($p^{(i)}$, Δ, and λ) we noticed an increase of CC, however combined with unsatisfactory QI.

Table 5. The results of FHR recordings classification using LSVM method ($\gamma = 800, \sigma = 0.04$) with learning based on the data with highest degree of certainty (highest fuzzy score).

Reference fetal state	$p^{(i)}$	Δ	λ	CC	QI
SaN					
Apgar score	0.75	0.00	0.5	67.47	41.74
pH	0.25	0.25	0.3	88.89	82.04
SaP					
Birth weight	0.75	0.00	0.5	68.42	60.48
Apgar score	0.75	0.00	0.5	75.20	70.93
pH	-0.75	-0.25	0.0	83.60	74.52
Fuzzy assessment	-0.75	0.50	0.3	89.42	80.31

4.3. COMPUTATIONAL EFFECTIVENESS AND CUDA

To improve the computational effectiveness of the solution, the LSVM algorithm was implemented using Compute Unified Device Architecture (CUDA). In the experiments, the HP Z400 workstation with the Intel Xeon W3670 processor (3.20 GHZ) and a graphic card NVidia Quadro 5000 was used. For the considered set of data, calculations made on GPUs led to a decrease of the computing performance – time cost of data transfer to the graphic card memory were higher than benefits resulting from making parallel computations (Table 6). However, the same algorithm applied for learning sets containing 700 and more recordings was performed faster on graphic processors. Using CUDA, the LSVM classification of 1000 recordings is conducted twice as fast, whereas the dataset containing 5000 recordings almost five times faster.

Table 6. The time (in seconds) of LSVM classification using GPU and CPU (calculated as a mean for fifty runs).

No. of recordings in training dataset	100	200	500	1000	5000
GPU	0.0666	0.0672	0.0823	0.1412	4.9343
CPU	0.0041	0.0143	0.0555	0.3205	23.329

5. CONCLUSIONS

The objective of this study was to investigate the possibility of a retrospective fetal state evaluation based on an analysis of neonatal outcome attributes. Consequently, a fuzzy reasoning system defining the relationships between newborn attributes and the resulting neonatal outcome assessment was proposed. A proper selection of the inference parameters made it possible to obtain high quality results of fuzzy reasoning in relation to the neonatal outcome evaluation determined on the basis of single newborn attributes. The fuzzy analysis was used in the process of the qualitative assessment of the fetal state using the Lagrange support vector machine. The application of fuzzy reference resulted in the improved classification quality when compared with learning based on a single newborn attributes evaluation. The proposed method allows for the integration of information included in the values of different newborn attributes aimed at determining a retrospective fetal state evaluation for the purpose of a qualitative assessment of fetal heart rate signals based on supervised learning algorithms.

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