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IMPROVING THE EFFICACY OF AUTOMATED FETAL STATE ASSESSMENT WITH FUZZY ANALYSIS OF DELIVERY OUTCOME

A number of methods of the qualitative assessment of fetal heart rate (FHR) signals are based on supervised learning. The classification methods based on the supervised learning require a set of training recordings accompanied by the reference interpretation. In the real data collections the class of signals related to fetal distress is usually under-represented. Too small percentage of distress patterns adversely affects the effectiveness of the automated evaluation of the fetal state. The paper presents a method of equalizing the class sizes based on the reference assessment of the fetal state with the fuzzy analysis of the newborn attributes. The supervised learning with increased number of the FHR signals, which are characterized by the highest rate of the fuzzy inference leads to significant increase of the efficacy of the qualitative assessment of the fetal state using the Lagrangian support vector machine.

1. INTRODUCTION

In the past, fetal movements perceived by mother were the only witness of life of a child in uterus. Currently, electronic monitoring of the fetal state is an essential part of modern medical care during pregnancy and labour. The recording and analysis of the fetal heart rate (FHR) are of particular importance for the accurate assessment of the fetal state. The proper fetal heart rate indicates an appropriate blood circulation, and thus good oxygenation and the intact functioning of the fetal central nervous system.

One of the most important biophysical methods of FHR signal acquisition is the Doppler ultrasound method. The ability for the correct interpretation of the FHR recordings is essential for the proper evaluation of the fetal state. The complexity of curves representing the FHR variability makes the accurate interpretation difficult [14]. Hence, the computer analysis providing a comprehensive quantitative description of the characteristic patterns that may occur in the signal is used to improve the reproducibility and objectivity of the evaluation. However, features of the FHR signal that are considered to be abnormal may be related with both fetal wellbeing as well as fetal distress. Hence, the constant interest for new procedures of automated assessment that could allow for increasing the efficacy of the final diagnosis.

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Many methods of the automated qualitative assessment of the fetal state are defined as supervised learning procedures. The supervised learning requires a corresponding set of reference FHR signals to identify the appropriate settings of the classifier. In this group one can distinguish algorithms based on artificial neural networks [13], [16], [17], neuro-fuzzy systems [6], [7], support vectors machines (SVMs) [10], [24], random forests [21], [23] and procedures that combine two or more different methods of data analysis [5], [26]. When analyzing the real collections of FHR signals the main problem is the insufficient number of recordings corresponding to fetal distress [15]. Large disproportion between the number of recordings indicating the fetal wellbeing and the fetal distress adversely affects the final results of classification. The equalization of the class sizes can be achieved by an appropriate duplication of reference patterns indicating the fetal health risk [7]. The proposed method is based on a retrospective assessment of the fetal state by the means of the fuzzy analysis of the newborn state attributes. The result of fuzzy inference allows for choosing the signals related to the fetal distress that are characterized with the highest diagnostic value - the highest fuzzy score. These signals, randomly added to the training sets of the Lagrangian Support Vector Machine (LSVM) [18], increase the efficacy of the automated fetal state evaluation with the LSVM supervised learning.

2. Retrospective analysis of fetal state

The qualitative assessment of the FHR signal involves assigning it to one of two classes, defining the fetal state as wellbeing or distress. Several studies distinguish also the third, indecisive class of fetal state named as ”suspicious”, identifying the cases which require further investigation. There is no other noninvasive diagnostic method, which allows for confirming the outcome of the fetal evaluation at the time of the FHR signal acquisition. The actual fetal state will be known only just after the delivery. In perinatology it is assumed however, that the fetal state can not change rapidly during pregnancy [20]. Hence, the results of the newborn state assessment can be used as the reference to verify the efficacy of the automated classification. The newborn state can be determined based on the analysis of the newborn attributes. There are three main attributes to be evaluated by a physician: the birth weight (BW) expressed in percentiles in relation to a given population of newborns, Apgar score (AP) representing the result of the visual assessment of the newborn, and measurement of the acid-base balance of the umbilical cord blood, expressed by the value of the negative logarithm of the hydrogen ion activity (pH). For each of these attributes there are ranges of values related to the distinguished classes of the newborn state (Table 1).

The supervised learning is usually carried out on the basis of a single attribute values. However, in such a solution, the information of the newborn state, which can be obtained as a result of the simultaneous analysis of all indicators is lost. Another approach is the application of the logical function whose attributes are values of binary evaluation of the selected attributes [16]. This paper describes the algorithm for the assessment of the degree of certainty of retrospective assessment of the fetal state based on the fuzzy inference [8]. The results of the fuzzy analysis determine the diagnostic value of the final assessment of the newborn state for the methods of automated fetal state evaluation based on supervised learning principles.

3. Fuzzy analysis

The fuzzy analysis of the newborn state is conducted on the basis of fuzzy conditional rules with three inputs, being the values of newborn attributes, and one output representing the

Table 1. The class labels of the newborn state attributes.

Newborn state	Newborn state attributes		
	BW	AP	PH
Wellbeing	≥ 10	≥ 7	≥ 7.2
Suspicious	$(5, 10)$	$[5, 6]$	$[7.1, 7.2]$
Distress	≤ 5	< 5	< 7.1

newborn state:

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

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 the pH measurement, and $A_j^{(i)}$ are the linguistic values (terms) defined by fuzzy sets that are characterized by trapezoid membership functions. The linguistic values represent the class of neonatal outcome being the result of the assessment of a single newborn attribute.

The parameters of trapezoidal membership functions $\mu_{A_j}^{(i)}(x)$ are determined based on the statistical analysis of the available dataset of newborn attributes [8]. The core of the fuzzy set is defined as the interquartile range of parameters values of the particular class of neonatal outcome. The limit values are calculated to fulfill the assumption that the membership of the values defining the boundary between classes should be the same and equal to 0.5 for both classes.

The symbol Y denotes the output linguistic variable representing the neonatal outcome. The linguistic values of the output variable are the natural language terms describing the class of the newborn assessment: "normal", "suspicious" and "abnormal". These values are defined by means of fuzzy sets $B^{(i)}$ with triangular membership function. In the proposed solution the membership functions are in the form of isosceles triangles with a base width equal to 2. The position of the centre of gravity location of the triangle $y_0^{(i)}$ is defined by assuming that a normal neonatal outcome corresponds to negative $y_0^{(i)} = -1$, whereas the abnormal to positive output value of a single fuzzy rule. To classify neonatal outcome as suspicious $y_0^{(i)} = 0$ is assumed (Figure 1).

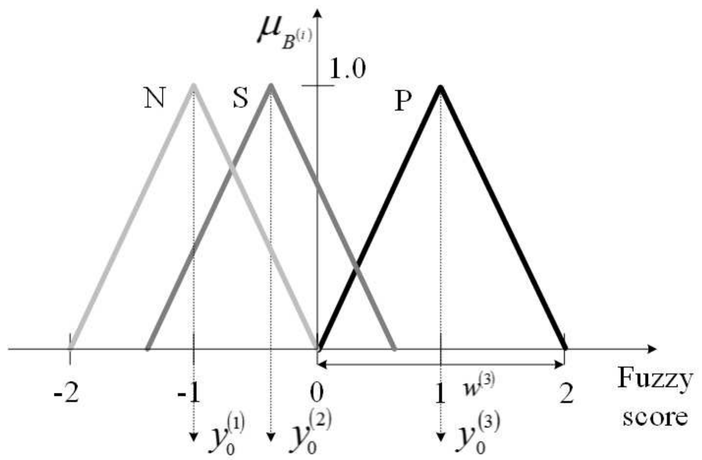

Fig. 1. An example of triangular membership function of output fuzzy sets (N - denotes the normal, S – the suspicious, and A – the abnormal neonatal outcome).

A complete rule base of the fuzzy reasoning system consists of $I = 3^3 = 27$ conditional statements, which define the relationship between single newborn attributes and the final neonatal outcome evaluation. In the proposed solution, the neonatal outcome is described as:

- abnormal, if any of attributes indicates the newborn distress,
- normal, if two or more attributes indicate the newborn wellbeing,
- suspicious, for all the remaining cases.

The fuzzy system is based on Larsen's fuzzy inference 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:

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

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

The arithmetic mean is applied as the aggregation operator and the crisp output is determined in the process of defuzzification using the centre of gravity method. Consequently, the final crisp output value is given as:

$$y_0 = \frac{\sum_{i=1}^{I} F^{(i)}\left(\mathbf{x}_0\right) y_0^{(i)}}{\sum_{i=1}^{I} F^{(i)}\left(\mathbf{x}_0\right)}, \tag{3}$$

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

The final result of the inference (fuzzy score) may be interpreted as a degree of certainty in relation to the retrospective fetal state evaluation based on newborn attributes analysis. This particular piece of information may be used for the selection of distress patterns with the highest diagnostic value (highest fuzzy score). The class sizes of the fetal state can be equalized by randomly resampling these patterns in the training set. Consequently the improved effectiveness of the qualitative assessment of the fetal state using the supervised learning can be achieved.

In the presented study we considered the binary classification problem assuming the attributes relating to the suspicious class of fetal state as representing the fetal wellbeing. Finally, the negative fuzzy system output y_0 defines the wellbeing while $y_0 \geq 0$ the fetal distress.

4. Qualitative assessment

In the proposed approach the qualitative assessment of the fetal state is determined using the support vector machine (SVM). The SVM procedures have been found to be successful when used for FHR signal classification [5], [9], [10], [24]. In practical solutions the learning speed is of special importance. Hence, we used a modified algorithm of support vectors - the Lagrangian Support Vector Machine [18]. In the LSVM procedure the quadratic programming is replaced with the iterative scheme. It results in lower computational complexity compared to the classical procedure SVM, while maintaining the high classification efficacy. The non-linear classification problem was solved using kernel functions in a radial form. The dispersion σ of the kernel is the algorithm parameter.

The classification efficacy was evaluated on the basis of confusion matrices with a help of classical prognostic indices such as percentage of the correct classifications (CC) of the signals from the testing set, sensitivity (SE), specificity (SP) as well as positive (PPV) and negative predictive values (NPV). To make the assessment of the learning results easier we introduced also the classification quality index (QI) defined as the geometric mean of SE and SP:

$$QI = \sqrt{SE \cdot SP}. \tag{4}$$

5. RESEARCH MATERIAL

The research material used in our experiments is the collection of the FHR signals from the one-hour fetal monitoring sessions. Each input vector consisted of the parameters that quantitatively describe the fetal heart rate signals. The corresponding newborn attributes were read from the neonatal forms [15]. The FHR signals were recorded using HP 50 series monitor from the patient abdomen via external pulsed Doppler ultrasound transducer. The raw research material was analyzed 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 685 antenatal recordings with the mean gestational age of 33 weeks, which were derived from 196 patients.

The selection of the FHR signal features of highest discrimination capacity is not an easy task. The studies shows the solutions based on the ROC analysis [4], correlation methods [19], [22], neural networks [22] or more even advanced methods [1], [12]. Not only the classical signal features in time and frequency domains are evaluated, but also the nonlinear parameters [1], [3], [11], [22]. However, the novel FHR signal description is not always easy to convert into knowledge useful for a medical diagnosis. The parameters from the time domain still remain the basis for qualitative fetal assessment. Hence, as fuzzy system inputs we used eleven classical parameters of the quantitative description of FHR signal, which are essential when assessing the fetal state:

1) the mean value of the FHR baseline bFHR [bpm] [25],
2) the fluctuation range bFHRr [bpm] of baseline values calculated as a difference between the maximum and minimum values,
3) the number of identified acceleration patterns ACC [1/h],
4) the number of identified deceleration patterns DEC [1/h],
5) the duration of the low variability of the FHR signal, expressed as the percentage of the signal length,
6) the Dawes FHR short-term variability index STV [ms],
7) the Dawes FHR long-term variability index LTV [ms],
8) the quotient of STV and LTV,
9) the amplitude of FHR oscillation OSC [bpm],
10) the percentage of silent FHR oscillation (OSC $\leq$ 5 [bpm]) in a whole trace,
11) the percentage of saltatory FHR oscillation (OSC $\geq$ 25 [bpm]) in a whole trace.

Additionally we analyzed:

1) the number of fetal movements MOV [1/h] perceived by mother during the entire monitoring,
2) the number of detected uterine contractions UC [1/h] and,
3) the fetal gestational age GA during monitoring

In highly developed countries the percentage of newborns with recognized abnormal postnatal state is very low. Data derived from clinics is usually characterized by a higher number of pregnancies at risk, however in the analyzed research material the class of FHR recordings corresponding to the abnormal neonatal outcome and hence the fetal distress is under-represented. Our database includes 54 signals (8% of the analyzed dataset) indicating the fetal distress due to the low percentile of the newborn birth weight, 40 recordings (6%) related to the low Apgar score and 15 entries (2%) with the abnormal pH level. The total number of the fetal distress recordings is 92 (13%). It should be noted that there was no case that would be characterized by all newborn attributes in the ranges indicating the abnormal neonatal outcome. Studies on the efficacy of the supervised learning [2], [7] shown that the best classification results can be obtained if the percentage of the under-represented class is at least 20%. Hence, we studied the impact of the resampling of the fetal distress patterns on the LSVM classification efficacy.

The procedure for the random reproduction involving the fuzzy inference was performed in two stages. At first, we identified the recordings of the fetal distress characterized by the highest diagnostic value (fuzzy score $y_0 \geq 0.5$) using the proposed fuzzy inference system. The parameters quantitatively describing the selected FHR signals were randomly modified in the range of their standard deviation. In a second step, the new collection of patterns were added to the training set (the testing set remained unchanged), so that the proportion of signals corresponding to fetal distress was respectively 20, 30, 40 and 50% of the whole training data.

6. RESULTS AND DISCUSSION

The learning was performed for 50 random divisions of the dataset into two equal parts: training and testing. The classifiers settings were determined using the algorithm specification leading to the maximum QI calculated for the 10 first divisions. The classification results presented in tables represent the mean values determined for all 50 divisions. The parameters γ [18] and σ for the LSVM method were selected from the range $[10^{-3}, \ldots, 10^{4}]$ with steps $\{10^{-3}, 10^{-2}, \ldots, 10^{3}\}$ changed every decade. The convergence coefficient of the iterative algorithm for the Lagrange multipliers calculation was defined as $\alpha = 1.9/\gamma$.

In the first stage of our study the LSVM learning was carried out without resampling of the distress patters. As a reference the assessment of the fetal state based on the single newborn attribute was used. Additionally, we investigated the common approach in clinical practice that is to assume the neonatal outcome as abnormal, if at least one newborn attribute is outside the physiological range (OR). The classification results are shown in Table 2.

Table 2. The efficacy of the LSVM classification for different methods of the retrospective fetal state assessment.

	γ	$1/\sigma$	CC	QI	SE	SP	PPV	NPV
BW	8000	0.09	88.24	63.64	44.52	91.97	32.61	95.11
AP	10000	0.50	90.80	55.36	33.20	94.37	27.19	95.81
PH	7000	0.09	94.97	36.73	17.75	96.81	11.57	98.01
OR	7000	0.10	83.39	65.14	48.00	88.87	40.41	91.70

The classification efficacy varied with the change of the applied method of the retrospective fetal state assessment. The highest value of the overall quality index QI $= 65.1 \pm 4.38\%$ was achieved for the "OR" approach. The second highest QI was noticed for the analysis of the birth weight QI $= 63.6 \pm 6.48\%$. The lowest efficacy of the LSVM classifier (QI $= 36.7 \pm 19.30\%$) was obtained in relation to the results of the pH measurements. However, the learning based on pH evaluation allowed for the best accuracy of the fetal state evaluation CC $= 95.0 \pm 1.02\%$. Such a high discrepancy between QI and CC is due to the low number of recordings (15 in the entire dataset of 685 signals), indicating the newborn acidosis.

In the second stage of our experiments the recordings related to the fetal distress were resampled in the training sets. The increased proportion of the distress patterns without the preliminary fuzzy analysis did not improve the classification results. The improve of the QI was obtained only if the reference fetal state was defined using the AP approach. The maximum value QI $= 57.9 \pm 9.90\%$ was noticed when the proportion of signals corresponding to the low Apgar score was equal to 30%.

Table 3 shows the classification results when the LSVM learning was based on the increased proportion of the distress patterns with the highest fuzzy score ($y_0 \geq 0.5$).

Table 3. The efficacy of the LSVM classification for the learning with resampled distress patterns which were characterized by the high value of the fuzzy score.

	20%		30%		40%		50%	
	CC	QI	CC	QI	CC	QI	CC	QI
BW	86.58	62.61	85.84	66.61	80.93	76.12	74.71	77.72
AP	91.47	54.46	88.69	60.04	79.74	69.36	77.90	68.98
PH	91.14	44.20	89.31	46.15	88.52	49.56	71.29	56.87
OR	82.78	65.24	84.90	67.25	78.83	73.97	74.59	77.06

It can be noticed that the random resampling of the distress patterns with the highest diagnostic value leads to a significant increase of QI for all considered methods of reference fetal state interpretation if only the proportion of the distress signals is at least 30%. In the case of resampling at the level of 20% we got a slight decrease of QI (about 1%) for BW and AP approaches. The highest improvement of classification efficacy (over 20% increase of QI) was obtained in the case of pH measurement and the equal number of recordings indicating the fetal distress and fetal wellbeing in the training sets.

Unfortunately, with the increase of QI usually the decreases of the accuracy of classification (CC) was noticed. It is due to the increase in the number of the false positive assessments. In the case of medical applications, this cost is acceptable against the accompanying substantial increase of the classification sensitivity. A simultaneous improvement of the accuracy (CC) as well as overall classification quality (QI) was noticed for the AP and PH approaches with the learning based on the 30% resampled distress patterns.

7. Conclusions

In the presented study we investigated the possibility of increasing the efficacy of the qualitative fetal state evaluation on the basis of the fetal heart rate signal analysis with the support vector machine. The improvement of the supervised learning was achieved through resampling of the fetal distress patterns in the training sets. The resampling procedure was based on the results of the fuzzy inference (fuzzy score) whose task was to model the relationship between the attributes of the newborn state and the actual neonatal outcome. As the neonatal outcome can be retrospectively assigned to the fetal state at the time of the FHR signal acquisition, the fuzzy score can be interpreted as a degree of certainty that one possesses in relation to the reference fetal state evaluation based on newborn attributes analysis. Consequently, the proposed fuzzy system can identify the FHR recordings of the highest diagnostic value. The supervised learning, based on the training data with resampled FHR recordings related to the fetal distress that are characterized by a high score of the fuzzy analysis led to a significant increase of efficacy of the qualitative assessment of the fetal state using the Lagrangian support vector machine.

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BIBLIOGRAPHY

[1] ALAMEDINE D., KHALIL M., MARQUE C. Comparison of different EHG feature selection methods for the detection of preterm labor. Computational and Mathematical Methods in Medicine, 2013, Vol. 2013. pp. 1–9.

[2] CATLEY C., FRIZE M., WALKER C., PETRIU D. Predicting high-risk preterm birth using artificial neural networks. IEEE Trans. Information Technology in Biomedicine, 2006, Vol. 10. pp. 540–549.

[3] CHUDACEK V., SPILKA J., JANKU P., KOUCKY M., LHOTSKA L., HUPTYCH M. Automatic evaluation of intrapartum fetal heart rate recordings: a comprehensive analysis of useful features. Physiol. Meas., 2011, Vol. 32. pp. 1347–1360.

[4] CZABANSKI R., JEZEWSKI J., HOROBA K., JEZEWSKI M. Fetal state assessment using fuzzy analysis of the fetal heart rate signals – agreement with the neonatal outcome. Biocybern. Biomed. Eng., 2013, Vol. 33. pp. 145–155.

[5] CZABANSKI R., JEZEWSKI J., MATONIA A., JEZEWSKI M. Computerized analysis of fetal heart rate signals as the predictor of neonatal acidemia. Expert Systems with Applications, 2012, Vol. 39. pp. 11846–11860.

[6] CZABANSKI R., JEZEWSKI M., WROBEL J., HOROBA K., JEZEWSKI J. Neuro-fuzzy approach to the classification of fetal cardiotocograms. IFMBE Proc. 14th Nordic Baltic Conference on Biomedical Engineering and Medical Physics, Riga, 2008. pp. 446–449.

[7] CZABANSKI R., JEZEWSKI M., WROBEL J., JEZEWSKI J., HOROBA K. Predicting the risk of low-fetal birth weight from cardiotocographic signals using ANBLIR system with deterministic annealing and ε-insensitive learning. IEEE Trans. on Information Technology in Biomedicine, 2010, Vol. 14. pp. 1062–1074.

[8] CZABANSKI R., WROBEL J., JEZEWSKI J. Fetal state evaluation with fuzzy analysis of newborn attributes using CUDA architecture. Journal of Medical Informatics and Technologies, 2013, Vol. 12. pp. 125–133.

[9] ESFANDIARI N., BABAVALIAN M., MOGHADAM A.-M., TABAR V. Knowledge discovery in medicine: Current issue and future trend. Expert Systems with Applications, 2014, Vol. 41. pp. 4434–4463.

[10] GEORGOULAS G., STYLIOS C., GROUMPOS P. Predicting the risk of metabolic acidosis for newborns based on fetal heart rate signal classification using support vector machines. IEEE Trans. on Biomedical Engineering, 2006, Vol. 53. pp. 875–884.

[11] GEORGOULAS G., STYLIOS C., GRUMPOS P. Investigation and comparison of different scale dependent features for fetal heart rate classification. Proceedings of the 16th International Federation of Automatic Control World Congress, Prague, Czech Republic, (CD-ROM), 2005.

[12] INBARANI H., NIZAR BANU P., AZAR A. Feature selection using swarm-based relative reduct technique for fetal heart rate. Neural Computing and Applications, 2014, Vol. 25. pp. 793–806.

[13] JADHAV S., NALBALWAR S., GHATOL S. Modular neural network model based foetal state classification. Proceedings of the IEEE International Conference on Bioinformatics and Biomedicine Workshops, Atlanta, United States, 2011.

[14] JEZEWSKI J., WROBEL J., HOROBA K., GACEK A., SIKORA J. Fetal heart rate variability: clinical experts versus computerized system interpretation. Proc. 24th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Huston, 2002. pp. 1617–1618.

[15] JEZEWSKI J., WROBEL J., HOROBA K., GRACZYK S., GACEK A., SIKORA J. Computerized perinatal database for retrospective qualitative assessment of cardiotocographic traces. Proc. Healthcare Computing Conference HC96, BJHC Ltd, Great Britain, 1996. pp. 187–196.

[16] JEZEWSKI M., CZABANSKI R., WROBEL J., HOROBA K. Analysis of extracted cardiotocographic signal features to improve automated prediction of fetal outcome. Biocybernetics and Biomedical Engineering, 2010, Vol. 30. pp. 39–47.

[17] JEZEWSKI M., WROBEL J., LABAJ P., LESKI J., HENZEL N., HOROBA K., JEZEWSKI J. Some practical remarks on neural networks approach to fetal cardiotocograms classification. Proc. 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Lyon, 2007. pp. 5170–5173.

[18] MANGASARIAN O., MUSICANT D. Lagrangian support vector machines. Journal of Machine Learning Research, 2001, Vol. 1. pp. 161–177.

[19] MENAI M., MOHDER F., AL-MUTAIRI F. Influence of feature selection on naive bayes classifier for recognizing patterns in cardiotocograms. Journal of Medical and Bioengineering, 2013, Vol. 2. pp. 66–70.

[20] ROOTH G. Guidelines for the use of fetal monitoring. Int. J. Gynecol. Obstet., 1987, Vol. 25. pp. 159–167.

[21] SAHIN H., SUBASI A. Classification of the cardiotocogram data for anticipation of fetal risks using machine learning techniques. Applied Soft Computing, 2015, Vol. 33. pp. 231–238.

[22] SPILKA J., CHYDACEK V., KOUCKY M., LHOTSKA L., HUPTYCH M., JANKU P., GEORGOULAS G., STYLIOS C. Using nonlinear features for fetal heart rate classification. Biomedical Signal Processing and Control, 2012, Vol. 7. pp. 350–357.

[23] TOMAS P., KROHOVA J., DOHNALEK P., GAJDOS P. Classification of cardiotocography records by random forest. 36th International Conference on Telecommunications and Signal Processing (TSP), 2013. pp. 620–923.

[24] WARRICK P., HAMILTON E., PRECUP D., KEARNEY R. Classification of normal and hypoxic fetuses from systems modeling of intrapartum cardiotocography. IEEE Transactions on Biomedical Engineering, 2010, Vol. 57. pp. 771–779.

[25] WROBEL J., HOROBA K., PANDER T., JEZEWSKI J., CZABANSKI R. Improving the fetal heart rate signal interpretation by application of myriad filtering. Biocybernetics and Biomedical Engineering, 2013, Vol. 33. pp. 211–221.

[26] YILMAZ E., KILIKCIER C. Determination of fetal state from cardiotocogram using LS-SVM with particle swarm optimization and binary decision tree. Computational and Mathematical Methods in Medicine, 2013, Vol. 2013. pp. 1–8.