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THE INFLUENCE OF CARDIOTOCOGRAM SIGNAL FEATURE SELECTION METHOD ON FETAL STATE ASSESSMENT EFFICACY

Cardiotocographic (CTG) monitoring is a method of assessing fetal state. Since visual analysis of CTG signal is difficult, methods of automated qualitative fetal state evaluation on the basis of the quantitative description of the signal are applied. The appropriate selection of learning data influences the quality of the fetal state assessment with computational intelligence methods. In the presented work we examined three different feature selection procedures based on: principal components analysis, receiver operating characteristics and guidelines of International Federation of Gynecology and Obstetrics. To investigate their influence on the fetal state assessment quality the benchmark SisPorto® dataset and the Lagrangian support vector machine were used.

1. INTRODUCTION

Cardiotocographic (CTG) monitoring is a method of biophysical assessment of fetal state during pregnancy and labor. It consists in acquisition and analysis of fetal heart rate (FHR), uterine contractions and fetal movements signals. Visual analysis of registered signals is difficult [11], so computerized fetal monitoring systems offering quantitative signal analysis are used. Despite increasingly advanced algorithms of the quantitative signal description, effective procedures of qualitative fetal state assessment are still the aim of research. Computational intelligence methods are applied to help in medical data analysis [8], also to CTG data. The literature shows the examples of cardiotocograms classification with fuzzy systems [22], [4], artificial neural networks [10], [18], [13], neuro-fuzzy systems [7], [20], [6] and support vector machines (SVMs) [19], [25]. The effectiveness of classification is highly dependent on the proper selection of features. Different studies [3], [24], [19], [17], [12] investigated the influence of the CTG features selection on the assessment quality of the fetal state. In the presented paper, we applied three different feature selection methods: principal components analysis (PCA), receiver operating characteristics (ROC) and guidelines of International Federation of Gynecology and Obstetrics (FIGO). The influence of the applied procedures on the fetal state assessment quality was verified with the benchmark CTG dataset [1] using the Lagrangian support vector machine (LSVM) [15].

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2. Material and methods

2.1. The CTG dataset

The research material used in our study is the SisPorto® dataset of CTG signals from UCI Machine Learning Repository [2] (obtained from `http://archive.ics.uci.edu/ml/datasets/Cardiotocography` in August 2013). It consists of 2126 signals described by 21 quantitative parameters (Table 1). The reference signal assessment was determined by three expert obstetricians and a consensus classification label was assigned to each of the cardiotocograms. Classification was both with respect to a morphological pattern (10 classes) and to a fetal state (3 classes: Normal (N), Suspect (S), Pathological (P)). Therefore, the dataset can be used either for 10-class or 3-class experiments. In the presented work the experiments concerning the three-class classification problem were performed. The respective numbers of cases in the distinguished classes of signal patterns are the following: 1655 (N), 295 (S), 176 (P). Research on the three-class classification of the SisPorto® dataset was also presented in [17], [25]. The binary classification problem after rejecting the Suspect class was shown in [19], [20] as well.

Table 1. The quantitative description of the considered set of CTG signals.

LB	FHR baseline (beats per minute)	**AC**	no. of accelerations per second
FM	no. of fetal movements per second	**UC**	no. of uterine contractions per second
DL	no. of light decelerations per second	**DS**	no. of severe decelerations per second
DP	no. of prolonged decelerations per second	**ASTV**	percentage of time with abnormal short term variability
MSTV	mean value of short term variability	**ALTV**	percentage of time with abnormal long term variability
MLTV	mean value of long term variability	**Width**	width of FHR histogram
Min	minimum of FHR histogram	**Max**	maximum of FHR histogram
Nmax	no. of histogram peaks	**Nzeros**	no. of histogram zeros
Mode	histogram mode	**Mean**	histogram mean
Median	histogram median	**Variance**	histogram variance
Tendency	histogram tendency		

2.2. Feature selection methods

Principal component analysis (PCA). On the basis of the original dataset the PCA method [16] creates a new set of features, called principal components. Each principal component is a linear combination of original features and all principal components are orthogonal to each other. The first principal component is chosen in such a way that its variance is the maximum among all possible choices. The second principal component is chosen so that to be perpendicular to the first and to have the maximum variance among all possible choices. The maximum number of principal components is the same as the number of original features however, the sum of variances of first few principal components often explains most of the total variance of the original data. The PCA may be performed using covariance or correlation matrix. In the presented work the correlation matrix was used. Features **Nmax**, **Nzeros**, **Tendency** were excluded from PCA processing due to their discrete character. The number of principal components which explain 90% of the total variance was chosen.

Receiver operating characteristics (ROC). ROC are two-dimensional graphs where true positive rate (sensitivity) is plotted against false positive rate (1-specificity) as a classifier discrimination threshold is varied [9]. The area under the ROC curve (AUC) is a popular measure of a classifier performance. Its value varies within the range [0, 1]. The higher value of AUC of a given classifier, the higher performance it has. In the presented work ROC was applied to assess predictive capabilities of all 21 CTG features [5]. According to the scale of predictive capabilities [5] it was assumed to choose features with AUC ≥ 0.7 for the further assessment.

Guidelines proposed by International Federation of Gynecology and Obstetrics (FIGO). FIGO proposed guidelines concerning electronic fetal monitoring [21]. Among many recommendations, they describe also criteria of cardiotocograms interpretation based on the evaluation of the CTG signal. The FIGO criteria include the assessment of baseline, long term variability, accelerations and decelerations episodes. Uterine contractions are also taken into consideration. In our research we applied the features that correspond to FIGO recommendations (Table 8).

The applied feature selection methods represent various approaches for determining the best discriminant set of the CTG signal features. PCA analyzes only relations between classifier inputs (features) and does not take into consideration a cardiotocogram class. Information described by ROC in the assumed manner is determined based on the relation between the cardiotocogram class and the given single feature value as its discrimination threshold is varied. Features selected with FIGO guidelines are chosen on the basis of the medical expert knowledge.

2.3. CLASS-CLASS METHODOLOGY

To assess the fetal state we used the Lagrangian support vector machine [15] binary classifier with the Gaussian kernel function $K(\mathbf{x}, \mathbf{x}_i) = \exp\left(-\chi \|\mathbf{x} - \mathbf{x}_i\|^2\right)$; where $\chi \in \mathbb{R}_+$ is the kernel parameter. LSVM is a technique for training support vector machines in which the quadratic programming was replaced with computationally efficient iterative approach. To perform the three-class classification, the class-class (one-against-one) methodology was applied. According to it, the fetal state assessment is the result the CTG signal evaluation with three binary classifiers distinguishing cases ($\mathbf{x}_i$): Normal and Suspect (NS), Normal and Pathological (NP), and Suspect and Pathological (SP). For each binary classifier, the processed input vector need to be properly labeled. In the presented study we used: N = +1, S = -1 for NS, N = +1, P = -1 for NP, and S = +1, P = -1 for SP classifier. The resulting desired outputs of binary classifiers are shown in Table 2.

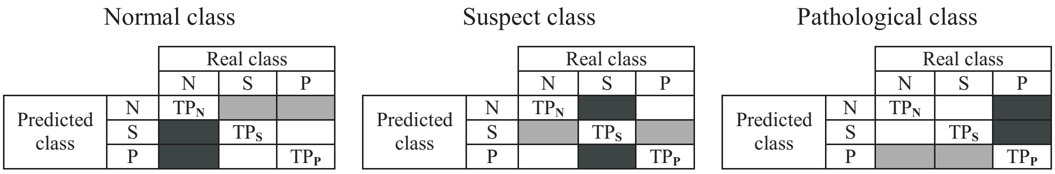
Table 2. Binary classifiers of CTG signals.

NS	NP	SP
$\mathrm{NS}(\mathbf{x}_i) = \begin{cases} > 0, & \mathbf{x}_i \in \mathrm{N}, \\ \leq 0, & \mathbf{x}_i \in \mathrm{S}, \end{cases}$	$\mathrm{NP}(\mathbf{x}_i) = \begin{cases} > 0, & \mathbf{x}_i \in \mathrm{N}, \\ \leq 0, & \mathbf{x}_i \in \mathrm{P}, \end{cases}$	$\mathrm{SP}(\mathbf{x}_i) = \begin{cases} > 0, & \mathbf{x}_i \in \mathrm{S}, \\ \leq 0, & \mathbf{x}_i \in \mathrm{P}. \end{cases}$

The three-class assessment of the fetal state is determined according to the Table 3. For inconclusive cases (marked by the symbol $\times$) the label provided by the binary classifier with the highest absolute value of discriminant function is assumed as the final result.

Table 3. Rules of assigning the final result of the fetal state evaluation.

	Binary classifiers answer							
NS	S	S	S	S	N	N	N	N
NP	P	P	N	N	P	P	N	N
SP	P	S	P	S	P	S	P	S
Fetal state	P	S	$\times$	S	P	$\times$	N	N



White: TN$_N$, Light grey: FP$_N$, Dark grey: FN$_N$

White: TN$_S$, Light grey: FP$_S$, Dark grey: FN$_S$

White: TN$_P$, Light grey: FP$_P$, Dark grey: FN$_P$

Fig. 1. The confusion matrices for the three-class classification problem (N: $i = 1$, S: $i = 2$ and P: $i = 3$).

2.4. The learning procedure

For the purpose of the correct LSVM classification, the considered dataset was normalized to the range [–1, +1]. Next each class of cases was 50 times randomly divided in learning (50%) and testing (50%) part to form learning and testing subsets for binary classifiers. In case of odd number of cases in a given class, additional case was added to the testing part. Using first 5 pairs of subsets, separately for each binary classifier, values of the LSVM parameter (ν) and kernel function (χ) ensuring the highest classification quality (QI, described in the next paragraph) were chosen from the set $\{0.001, 0.004, 0.007, 0.01, 0.04, 0.07, 0.1, \ldots, 700, 1000\}$. The rest of LSVM parameters was set to default [15]. Having established values of ν and χ, we evaluated each of binary classifier using remaining 45 pairs of learning and testing subsets. The final testing subset for the three-class classification problem was formed by merging the 45 testing parts of three classes with original class labels.

The performance of the binary classifiers was assessed based on the confusion matrices. The classification accuracy (CA) was defined as the percentage of correctly classified cases from the testing subset. The class labeled as –1 (S in NS, P in NP and SP classifiers) was considered as "positive" in calculation of sensitivity (SE) and specificity (SP). To make the analysis of the classification results easier we applied also the overall quality index ($\mathrm{QI} = \sqrt{\mathrm{SE} \cdot \mathrm{SP}}$). The final performance of three-class classification was measured with indices [23] presented in the Table 4. In the presented work all considered measures are expressed in percents. Quantities TP$_i$, TN$_i$, FP$_i$, FN$_i$ are calculated [14] for a given class (N: $i = 1$, S: $i = 2$ and P: $i = 3$) - see figure 1.

Table 4. Performance measures of three-class classification.

$\mathrm{AE} = \frac{\sum_{i=1}^{3} \frac{\mathrm{TP}_i + \mathrm{TN}_i}{\mathrm{TP}_i + \mathrm{FN}_i + \mathrm{FP}_i + \mathrm{TN}_i}}{3}$	the average per-class effectiveness of a classifier
$\mathrm{SE}_M = \frac{\sum_{i=1}^{3} \frac{\mathrm{TP}_i}{\mathrm{TP}_i + \mathrm{FN}_i}}{3}$	the average per-class sensitivity
$\mathrm{SP}_M = \frac{\sum_{i=1}^{3} \frac{\mathrm{TN}_i}{\mathrm{FP}_i + \mathrm{TN}_i}}{3}$	the average per-class specificity
$\mathrm{QI}_M = \sqrt{\mathrm{SE}_M \cdot \mathrm{SP}_M}$	the average per-class quality index

2.5. Rejection of repeated and contradictory cases

As a result of the initial analysis of the research material entries with equal values of signal features were found. There were observed repeated cases (ReC) - representing the same class, and contradictory cases (CoC) - belonging to different classes. Consequently, we decided to apply three different classifier learning and testing approaches. Firstly, the unambiguous learning and testing subsets for a given feature vector (set) were prepared. To do that, from

ReC only one case was left, and all CoC were rejected. The following rejection procedure was applied:

1) Separate Normal, Suspect and Pathological class from the original dataset.
2) Leave only one ReC (for a given feature vector) in each class.
3) Merge obtained classes into a single dataset.
4) In the obtained dataset find and reject all CoC (for a given feature vector) obtaining unambiguous dataset.

The rejection procedure was performed for all 21 features and for a set of features selected with FIGO guidelines. PCA was performed on the unambiguous dataset obtained for the selected 18 features (after rejecting the discrete characteristics). In case of ROC there were three different feature sets, each for given binary classifier. In that case, the rejection procedure was firstly applied for NP classifier feature vectors. Next, using the obtained unambiguous dataset, the rejection procedure was applied for SP classifier feature set. In the last step, the feature set for the NS classifier was analyzed. Numbers of cases rejected applying all features and three feature selection methods are summarized in the Table 5.

Table 5. The number of rejected Repeated Cases (ReC) and Contradictory Cases (CoC).

	ReC	CoC	Total		
			N	S	P
ALL PCA	12	4	10	5	1
FIGO	14	4	11	5	2
ROC	27	6	20	9	4

The obtained unambiguous dataset was used to form unambiguous learning and testing parts of a given class and learning and testing subsets. The classification procedure using the resulting subsets was called ”unambiguous learning - unambiguous testing” (ULUT). In the second approach, cases rejected from a given class were 50 times randomly divided in half and added to existing 50 unambiguous learning and testing parts. Such procedure led to ”ambiguous learning - ambiguous testing” (ALAT) approach. Combination of unambiguous learning and ambiguous testing was called (ULAT). ULUT, ALAT and ULAT were performed for all features and for all applied feature selection methods. The sizes of learning (L) and testing (T) parts (ULUT) along with number of cases (in parenthesis) added to each part (ALAT and ULAT) are presented in the Table 6.

Table 6. Number of cases in learning (L) and testing (T) part for a given class of CTG signals.

	Normal		Suspect		Pathological	
	L	T	L	T	L	T
ALL PCA	822 (+5)	823 (+5)	145 (+2)	145 (+3)	87 (+0)	88 (+1)
FIGO	822 (+5)	822 (+6)	145 (+2)	145 (+3)	87 (+1)	87 (+1)
ROC	817 (+10)	818 (+10)	143 (+4)	143 (+5)	86 (+2)	86 (+2)

The presence of ReC and CoC in ALAT and ULAT subsets was verified. Table 7 presents statistics of number of pairs of ReC and CoC for the final testing subsets. In case of ROC the verification was done three times (for each binary classifier feature vector) and the presented values are averages.

Table 7. The number of pairs of ReC and CoC in final testing subsets for the ALAT and ULAT approaches.

	ALL	PCA	FIGO	ROC
ReC	4.3 (1.64)	4.0 (2.12)	5.1 (2.20)	5.5 (2.02)
CoC	0.5 (0.51)	0.8 (0.74)	0.5 (0.63)	0.7 (0.76)

mean value (standard deviation)

3. Results and discussion

In the first stage of our experiment we applied the proposed feature selection methods. Table 8 presents sets of features obtained for all considered procedures. Features of the quantitative description of CTG signals selected with PCA (10 new features) and FIGO (9 features) are common for all three binary classifiers. In case of ROC three different sets were determined (12 features for NS classifier, 7 for NP and 8 for SP).

Table 8. Features sets obtained for different selection methods.

	NS	NP	SP
ALL	all 21 features		
PCA	10 first principal components (92.25% of variance explained)		
FIGO	**LB**, **AC**, **UC**, **DL**, **DS**, **DP**, **ALTV**, **MLTV**, **Width**		
ROC	**LB**, **AC**, **UC**, **ASTV**, **MSTV**, **ALTV**, **Width**, **Min**, **Mode**, **Mean**, **Median**, **Variance**	**AC**, **DP**, **ASTV**, **MLTV** **Mode**, **Mean**, **Median**	**LB**, **DL**, **DP**, **MLTV**, **Min**, **Mode**, **Mean**, **Median**

Classification performance of binary classifiers and ULUT experiment is presented in the Table 9. In case of all applied feature selection methods the highest mean value of QI was obtained for NP, and the lowest for NS binary classifier. It suggests, that the correct distinction between Normal and Pathological is the easiest and between Normal and Suspect most difficult. In case of NS and NP smaller number of features (PCA, FIGO, ROC) leads to the lower mean value of QI. However, different feature selection methods decrease mean value of QI in a different degree. It seems that the cause is different number of features selected using ROC for these classifiers. For example, in case of NS mean value of QI decreases in the following order: ROC (12 features), PCA (10), FIGO (9). In case of NP the decreasing order is as follows: PCA (10 features), FIGO (9), ROC (8).

Results of three-class classification for ULUT experiment are presented in the Table 10. Smaller number of features (PCA, FIGO, ROC) leads to lower mean value of QI_M, similarly to QI for binary classifiers.

Table 11 compares results of mean value of QI_M obtained using ULUT, ULAT and ALAT approaches. The learning with unambiguous dataset results in improvement of the classification quality in most cases. Only with ROC based feature selection procedure the best results of the fetal state evaluation was obtained with the ALAT approach. The differences of the mean QI_M values are however irrelevant. The reason seems to be a very small number of ReC and CoC pairs in the ULAT and ALAT subsets (Table 7).

Since none of the applied feature selection methods increased the mean value of QI_M, to get the best quality of fetal state assessment all CTG signal features should be used. However, as the differences seems to be irrelevant, the feature space reduction may be regarded as decreasing the computational complexity of the classification procedure.

Research described in [17], [25] were also performed using the SisPorto® dataset. In [17] the influence of various feature selection methods on fetal state classification quality was examined. There, in contrast to our results, the application of the feature selection method

Table 9. The influence of the feature selection method on the performance of binary classifiers (ULUT approach).

		NS	NP	SP
		$\nu = 100$, $\chi = 1$	$\nu = 40$, $\chi = 0.1$	$\nu = 10$, $\chi = 1$
ALL	QI	85.30 (2.327)	94.63 (1.629)	89.93 (1.943)
	CA	93.52 (0.803)	98.61 (0.330)	90.98 (1.581)
		$\nu = 700$, $\chi = 0.7$	$\nu = 10$, $\chi = 1$	$\nu = 1$, $\chi = 7$
PCA	QI	83.00 (2.164)	94.34 (1.480)	90.67 (1.795)
	CA	92.32 (0.814)	98.60 (0.308)	91.92 (1.518)
		$\nu = 10$, $\chi = 1$	$\nu = 4$, $\chi = 100$	$\nu = 4$, $\chi = 7$
FIGO	QI	79.74 (2.349)	93.12 (1.538)	90.42 (1.311)
	CA	91.32 (0.594)	97.74 (0.372)	91.13 (1.193)
		$\nu = 1000$, $\chi = 0.4$	$\nu = 1000$, $\chi = 7$	$\nu = 7$, $\chi = 7$
ROC	QI	84.82 (2.519)	91.23 (2.533)	86.76 (2.078)
	CA	92.85 (0.827)	97.36 (0.516)	88.14 (1.719)

mean value (standard deviation)

Table 10. The influence of the feature selection method on the three-class classification performance (ULUT approach).

	ALL	PCA	FIGO	ROC
AE	94.62 (0.497)	93.98 (0.581)	93.07 (0.433)	93.75 (0.492)
SE_M	83.58 (1.701)	82.27 (1.751)	80.20 (1.783)	80.81 (1.876)
SP_M	92.68 (0.882)	91.76 (0.860)	90.24 (0.902)	92.38 (0.880)
QI_M	88.01 (1.244)	86.88 (1.285)	85.07 (1.350)	86.40 (1.344)

mean value (standard deviation)

Table 11. Comparison of the three-class classification quality QI_M.

	ALL	PCA	FIGO	ROC
ULUT	88.01 (1.244)	86.88 (1.285)	85.07 (1.350)	86.40 (1.344)
ULAT	87.95 (1.224)	87.56 (1.212)	85.15 (1.353)	86.39 (1.311)
ALAT	87.93 (1.187)	86.80 (1.258)	84.96 (1.420)	86.96 (1.367)

mean value (standard deviation)

increased accuracy, specificity and mainly sensitivity (from 87.24% to 91.58%). However, there is no detailed description concerning calculations of these quantities. In [25] the obtained confusion matrix was presented. As a result it is possible to calculate QI_M=86.74%. Since in [25] the original dataset was applied, we can use for the comparison the results from ULAT (QI_M=87.95%) or ALAT (QI_M=87.93%) approach when all features were assessed. It may be observed, that our results are slightly better.

4. Conclusions

In the presented research the influence of feature selection methods on the fetal state classification performance with Lagrangian support sector machine was examined. The benchmark SisPorto® set of cardiotocographic signals was used. Three different methods representing various approaches to the selection of the features of the quantitative description of CTG signals were investigated. However, the best results were obtained if all features were used as classifier inputs. We investigated also different approaches for the construction of the learning and testing data. Removing the ambiguous cases from a dataset that is used for the classifier learning increases slightly the classification quality for both, ambiguous and unambiguous testing. Such small improvement of the classifier is the result of small percentage of the ambiguous data in the considered research material. However, this subject will be the topic of our future investigations.

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