Tuning Support Vector Machines via Particle Swarm Optimization For The Classification Of Fetal Heart Rate Signals

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Abstract. In this paper we present a novel method for the classification of Fetal Heart Rate signals using a very powerful tool from the field of pattern recognition, the Support Vector Machines (SVMs), combined with Particle Swarm Optimization (PSO) for tuning the free parameters of the SVM. The proposed method was tested on a data set of intrapartum FHR recordings with promising results.

1 Introduction

Electronic fetal monitoring is an essential tool for fetal surveillance during labor. It includes monitoring and evaluation of the Fetal Heart Rate (FHR) in order to assess the fetal condition [1]. A lot of research efforts have been made towards the development of automatic and reliable methods for processing and evaluating FHR. This research work applies an integrated methodology for processing and classifying FHR based on the extraction and utilization of 3 categories of features and a powerful tool for classification from the field of pattern recognition, the Support Vector Machines (SVMs) [2]. In order to fully exploit the capabilities of SVMs we employ for the first time the technique of Particle Swarm Optimization [3], belonging to the broader class of evolutionary algorithms, in order to select the model parameters of the SVM. The results are very promising achieving high classification performance for the specific application.

2 Methods

There is an ongoing interest for more automated methods for FHR processing and analysis, which requires the research of methodologies for feature extraction and suitable classification methods so as to develop computer based systems able to analyse, classify and interpret the FHR [4]. However none of the already proposed procedures so far has been adopted in everyday clinical practise and this effort continuous striving for better (more reliable) methods.

In this research work we propose a method for the classification of FHR signal based on a combination of features extracted in three different domains: the time domain (7 features), the frequency domain (5 features) and 7 morphological features (extracted by conventional interpretation of the FHR based on its morphology) [5]. Those features are fed to a SVM to perform the classification of fetuses into 2 classes: the normal class and the “at risk” class.

2.1 Support Vector Machines

Support Vector Machines are learning systems that are trained using an algorithm based on optimization theory [2]. The decision function for a two-class problem is given by:

$$f(\mathbf{x}) = sign\left(\sum_{i=1}^{l} y_i \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b\right)$$

, where the coefficients a_i are optimized during training. Different machines with different nonlinear decision surfaces can be constructed, depending on the choice of the kernel function. Among the most popular kernel functions are: a) the Radial Basis Function kernels: $K(\mathbf{x},\mathbf{x}_i) = \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{x}-\mathbf{x}_i\|^2\right)$, where the width σ^2 is specified a priori by the user and is common for all the kernels, and b) the polynomial kernels of degree *d:* $K(\mathbf{x},\mathbf{x}_i) = \left(\langle \mathbf{x}\mathbf{x}_i \rangle + 1\right)^d$.

Apart from the selection of the σ in the case of RBF kernels and the degree d in the case of the polynomial kernels, there is another parameter; that is the value of the penalty weight C. The selection of the model and the corresponding parameters is performed usually through a cross validation technique [7] and a systematic test of a wide rage of the parameter space. In this research work instead of an exhaustive search of the parameter space we employ an algorithm from evolutionary computation in order to find a good set of parameters.

2.2 Particle Swarm Optimization

Particle swarm optimization (PSO) is a stochastic, population-based optimization algorithm. It is a derivative free optimization method and has been used with considerable success for many applications, including the training of neural networks [3]. The Basic PSO algorithm consists of the velocity and position equation:

$$v_i(t+1) = \phi(t)v_i(t) + \eta_1 r\left[p_i - x_i(t)\right] + \eta_2 r\left[p_{b(i)} - x_i(t)\right]$$
$$x_i(t+1) = x_i(t) + v_i(t)$$

, where *i* is the particle index, $v_i(t)$ is the current velocity of the i^{th} particle, $\phi(t)$ is an inertia function (usually a linearly decreasing one), $x_i(t)$ is the current position of the i^{th} particle, p_i is the position with the best fitness value visited by the i-th particle, $b(i)$ is the particle with the best fitness among all the particles (best position found so far-global version of the PSO), r is a positive constant called acceleration constant and η_1, η_2 are random numbers uniformly distributed in [0,1].

In our case the fitness function is the geometric mean of the accuracies observed separately on negative and positive examples [8] and the dimension of the position and velocity vector is 2. The first dimension corresponds to the kernel parameter (σ and d respectively, depending on the choice of the kernel) and the second dimension corresponds to the penalty parameter C.

3 Results

The proposed method was applied to a set of 80 FHR signals recorded during the intrapartum period, just a few minutes before delivery. The data set consisted of 60 signals belonging to fetuses with umbilical pH>7.2, representing the normal group, and 20 signals belonging to fetuses with pH<7.1, indicating an increased risk of developing hypoxia. To overcome the imbalance of the two data class, we applied oversampling of the minority class and for this purpose we used the Synthetic Minority Over-sampling Technique [6]. Table 1 summarises the results of the proposed method using SVMs with RBF kernels with the same penalty parameter (C) for both classes and for 400% oversampling of the minority class.

The performance of the proposed method was tested by using the 10-fold stratified cross validation and due to the stochastic nature of both the SMOTE and the PSO algorithm we repeated the procedure 5 times and averaged the results, which are summarized in the following table.

kernel	Accuracy (overall)	Accuracy (normal)	Accuracy (“at risk”)
RBF	86.87%	87.38%	85.33%
Polynomial	88.82%	89.54%	86.67%

Table 1. Classification results with 2 types of kernels

4 Discussion

The presented procedure is very promissing as it is indicated by these first results. The very demanding task of FHR anlysis and classification is further complicated by the imbalanced nature of the test sample. The proposed method with the combination of SMOTE to overcome the problem of imbalanced data and the tuning of the SVM classifier introducing the PSO method seems to be able to give a satisfactory solution to that problem. The SVM with the polynomial kernels seem to perform slightly better than the SVM with the RBF kernels and both of them achieve very good results.

5 Conclusions

In this research work we propose a novel integrated method for the problem of FHR analysis and classification. The well known for their generalization ability SVMs are leveraged both by the use of SMOTE and PSO and manage to achieve high performance for the categorization of FHR signals.

In future work we will also experiment with different penalty arameters for the 2 classes in an attemp to further increase the sensitivity of the method. Furthermore, we will also try to incorporate a feature selection stage since the dimensionality reduction of the input vector leads to an increase in generalization performance.

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