Detection of Fetal Distress though a Support Vector Machine Based on Fetal Heart Rate Parameters

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Abstract

This work aimed at realizing an automatic system for diagnosing fetal sufferance through advanced classification methods applied to reliable indexes extracted from fetal heart rate (FHR) recordings. We selected a set of FHR recordings from a database of 909 exams, which were supplied with the diagnosis at the delivery. The analysis was based on both classical parameters taken from the obstetrical clinical literature and some new indexes already used for HR variability in adults, like the power spectral density (PSD) and the approximate entropy (ApEn). This parameter set was then used as input of a learning machine based on the support vector machine (SVM) algorithm. We obtained a dichotomic classifier, performing the detection of suffering IUGR fetuses from healthy ones. A high percentage of correct classifications, above 84%, was reached by filtering the training set with only 65 of the starting 909 available records.

1. Introduction

One of the major problems of prenatal clinical monitoring is to detect as early as possible the presence of fetal distress and then to assess any critical situation for the fetus. Fetal distress conditions can be classified as chronic or acute. The chronic state is often characterized by anomalies of fetal nutrition and it is commonly associated to an alteration of fetal growth. The acute state can be distinguished by some aspects such as asphyxia of fetal unit and, differently from chronic state, it is usually a complication of the labor [1].

This study refers to chronic fetal distress which is a condition slowly evolving during the pregnancy period. Thus, the diagnosis of this problem at the right time is very important to protect fetal health.

Generally a fetal distress condition originates other related problems: suffering fetuses have dimension smaller than normal fetuses; they also present a delayed neural development. Physicians refer to this condition as IUGR (Intrauterine Growth Restriction).

Particularly, IUGR is diagnosed when some problems or abnormalities prevent cells and tissues from growing or cause cells to decrease in size. This may occur when the fetus does not receive the necessary nutrients and oxygen needed for its growth and development, or because of infections. In general [2], IUGR is characterized by reduction of the maternal-fetal respiratory exchanges, which mainly causes reduction of fetal blood oxygenation and heaps of carbon dioxide. Finally it induces a state of anaerobic metabolism which is associated to an increase of the acid metabolite concentration.

The cardiotocography (CTG) is the most widely used technique for evaluating fetal distress, including IUGR pathology, in the clinical routine [3]. A CTG exam consists of the simultaneous recording and analysis of fetal heart rate (FHR) and tocogram (uterine contraction). The clinical goal is to extract from the two tracings possible signs of fetal sufferance during pregnancy.

The wide diffusion of CTG for antepartum fetal monitoring has led to a reduction of intrapartum and child mortality. Nevertheless a high presence of many false positives and thus a high number of wrong caesarean sections still represents a serious problem that remains unsolved. This problem can be attributed to the lack of suitable parameters and methods to quantitatively evaluate CTG recordings [4].

Our project aims at providing clinicians with some automatic tools for analyzing CTG signals in order to diagnose any fetal suffering status, which can emerge antepartum.

The idea consists of identifying an array of numerical indexes by which it will be possible to classify pathological situations, in a reliable way [5]. Then the selected parameters are used as input for a learning machine to obtain a reliable classifier of fetal wellbeing condition.

Among the possible available algorithms, we chose to perform all the trials with the same classifier, based on the support vector machines (SVM) algorithm [6]. since it provided good quality results in a preliminary work.

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2. Methods

CTG database

The set of cardiotocographic tracings, available for developing this research work, consists of 1295 exams performed in four different clinics belonging to the University of Tor Vergata (Roma). These data have been processed in collaboration with the Dipartimento di Bioingegneria del Politecnico di Milano. Unfortunately, only 909 tracings were supplied with a complete diagnosis at delivery. Each of these exams included information regarding: gestational age, indication of a possible fetal sufferance, type of delivery (natural or caesarean section), and definite diagnosis at delivery. This information allowed us to subdivide the tracings in 332 normal fetuses, and 557 diagnosis of various pathological states (99 IUGR).

Parameters

In order to extract the diagnostic information from the CTG signals, we calculated a series of parameters as reported in [5] They refer to the physiological mechanisms that perform the control of the FHR signal.

Parameters might be grouped as:

- *Morphologic* -large and small accelerations per hour [7];
- *Time domain* - FHR mean over a minute (mean FHR), Delta, Short term variability (STV), Long term irregularity (LTI), Interval Index (II) [8];
- *Frequency domain* from autoregressive power spectrum estimation - LF-power, MF-power, HF-power and LF/(MF+HF)) [9].
- *Regularity* parameters – Approximate Entropy (ApEn) [10].

Since the final goal of this work is to investigate if it is possible to automatically detect fetal distress state from the value of multivariate variable, an initial set of nine parameters has been identified. This set represents the variable *x* which is used for the Support Vector Machine classification process, as reported in Table 1.

Table 1. FHR Parameters

Type	Parameter Name
Computed on whole signal	Large accelerations Small Accelerations
Computed on each 3 minutes segments	Mean FHR , LTI LF, MF, HF, LF/(MF+HF), ApEn
Computed on each minute in each 3 minutes segments	Delta STV Interval Index

Support Vector Machines

SVM is a powerful supervised learning algorithm belonging to the Statistical Learning Theory, which minimizes the Structural Risk performance on many classification problems.[6]

A classification task usually involves training and testing data, which consist of some data instances. Each instance in the training set contains one "target value" (class label, target value refers to the presence of fetal sufferance) and several "attributes" (features, in this work attributes are CTG parameters). The goal of SVM is to produce a model predicting target values of data instances in the test set, for which only the attributes are given.

Given a training set of instance-label pairs

$$(y_1, x_1),...,(y_n, x_n), x \in R^n, y \in \{-1,+1\},$$

the support vector machine (SVM) requires the solution of the following optimization problem:

$$\min\left(\frac{1}{2}(w \cdot w^T) + C\sum_{i=1}^{l}\xi_i\right)$$

subject to

$$y_i\left[(w \cdot \Phi(x_i)) + b\right] \geq 1 - \xi_i$$

where C (C > 0) is the penalty parameter of the error term, ξ is the parameter controlling the "tolerance" of misclassification (usually called "slack" variable). In the expressions reported above $\Phi(x_i)$ is a kernel function and it is used for non-linear problems. As a matter of fact, in non-linear problems, the training vectors are mapped into a higher (may be infinite) dimensional space. SVM finds a linear separating hyper-plane with the maximal margin in this higher dimensional space.

The procedure for building a SVM is quite simple. The first step performs the data scaling. Then the kernel function is defined (it can be polynomial, Radial Basis Function, etc.) and its parameters are determined. After a training phase, the classifier is tested with a validation set. This step is repeated a large number of times. The aim is to tune C and the kernel parameters in order to obtain the best performance of the classifier. Finally we test the model through a test set different from the validation set.

Protocols

In order to achieve the proposed goal, our study followed a heuristic method. Once the SVM classifier algorithm was chosen, we performed a set of trials, with different subsets of recordings and parameters, each time selecting the subsequent options on the basis of the previously obtained results.

The work was subdivided into protocols representing sets of choices. Each protocol is reported with a schematic description of the database filtering procedure, the input parameter subset and the obtained classification

accuracy. At the end of each protocol description, there was a brief evaluation of the obtained classifier and some consideration leading to the subsequent choices.

3. Results

Protocol 1

We tried to refine the starting data set to achieve a reduced group of exams with the best information content. So we considered only fetuses in the activity state, which is identified by i) presence of large accelerations (at least 15 bpm over the FHR baseline for at least 12.5 seconds), ii) presence of at least two small accelerations and iii) LTI value above 20ms. These options reduced the dataset to 638 exams.

Moreover, only exams performed between 30th and 35th gestational week were taken, because this period is crucial to decide if a premature birth (caesarean section) is necessary. Previous researches demonstrated the meaningfulness of entropy parameters for a reliable classification of such gestational class [11].

Furthermore we extracted only records with coherent values in the "kind of delivery", "antepartum diagnosis" and "final diagnosis" fields, since the SVM learning machine does not require to be supplied with known false-negatives and false-positives samples.

Trials and Results –Protocol 1

The selected parameters were FHR, II, Delta, STV, LTI, ApEn, LF, MF, HF, Spectral Ratio, Large accelerations, Small accelerations. We tried RBF and polynomial kernels (first degree).

The RBF kernel showed a good classification result with the training set (87.71%) and a poor generalization over the test set (only 50.74%). The polynomial kernel was less powerful than the RBF one and it was unable to learn and generalize well (train and test percentage were around 56-46%).

Filtering the input dataset by considering only normal fetuses with Apgar scores of 10-9 and pathological with 8-6 values, we obtained a slightly better performance.

Using the polynomial kernel, the classification score decreased to 74.5% while the successful test classifications percentage raised to 58.62%.

Discussion on protocol 1

The above-mentioned results show that the machine quickly reached an over trained state. The polarization of the classifier is clear, when comparing the extremely high classification score over the training set with the poor percentage on the test set, composed by examples not yet presented to the SVM.

Thus, we decided to provide the SVM with a smaller training set containing more specific informative contribution on the possible pathological state. This led to a restriction of the input space, that is our hypothesis domain, and to a restriction of the thesis of our implication.

We trained a SVM to extract information regarding only one pathological issue from the available data. Such a choice made our SVM less sensitive to possible statistical interactions of different unhealthy states. At the same time, the learning process became more specific in exploiting contribution of input information.

We adopted this strategy in protocol 2, where the classifier was focused to detect normal and IUGR fetuses only.

Protocol 2

We restricted the "ill-fetus" class to one of its sub-category, by choosing the IUGR condition, which is the most common and representative pathology in our former database. Moreover it has been assessed that many suffering pregnancies resulted in small fetuses.

The initial database was reduced to 597 recordings by selecting exams related to newborns with a IUGR delivery diagnosis or with a normal birth state.

We considered only tracings belonging to the 30- 35th gestational weeks, as in protocol 1.

As training set we selected the records corresponding to fetuses without any pathological diagnosis both antepartum and at delivery, born naturally (normal) and to fetuses delivered by caesarean section, with antepartum and delivery diagnosis IUGR-IUGR or Suffering-IUGR. Again, we considered only one tracing for each pregnancy week. At the end of this refining process, 65 recordings, subdivided in 30 normal and 35 pathological FHR signals, composed the database resulting by applying the protocol 2 specifications.

By considering the small number of cases satisfying all the imposed constraints, we retrieved 19 samples previously eliminated (among those closer to the acceptance) and included them as test set for our classifier.

Trials and Results – Protocol 2

Different tests were performed by selecting different sets of parameters. First, we reduced to nine the input parameters of the SVM, namely mean FHR, II, Delta, STV, LTI, ApEn, Spectral Ratio, Large and Small accelerations.

Over the train set, our SVM correctly detected 29 IUGR fetuses of 35 and 25 normal fetuses of the 30 present in data, with 11 misclassified records, obtaining thus a 83% success percentage. Examining the performances over the test set, we found 8/11 recognized pathological cases and 6/8 healthy (that is identifying only 3 false negatives and 2 false positives), reaching a 70% accuracy.

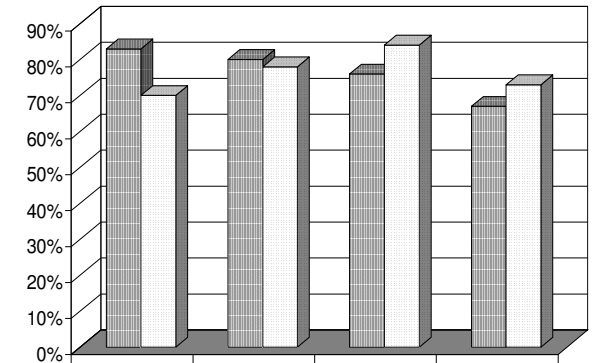
After a sensitivity analysis on the nine parameters we

reduced the input set to only seven parameters: LTI, ApEn, Spectral Ratio, Large accelerations, Small accelerations, FHR, Delta.

The resulting SVM, choosing C = 10, reached 80% correct classifications on the training set and 78% on the test set (3 false positives and 1 false negative) as shown in Figure 1. This result can be an indirect proof of the low significance of the two discarded parameters, the interval index (II) and the short-term variability (STV).

Since FHR and Delta (the FHR variation within one minute) are strictly related, we tested new SVMs with only six parameters: five fixed parameters (LTI, ApEn, Spectral Ratio, Large accelerations, Small accelerations) + FHR or Delta, respectively. Both the classifiers fed with six parameters performed well, especially the one with the FHR. It obtained 84% correct classifications on the test set (76 % on the training set) with a penalty parameter C=10.

Anyway, none of the above classifiers reached the same results of the 7-parameters one, at least not with the same C value (they performed almost similarly with C=20), as it can be appreciated in Figure 1 showing the summary of results.



	9 param	7 param	5+ fhr	5 + delta
Train	83%	80%	76%	67%
Test	70%	78%	84%	73%

Figure 1 – Summary of SVMs classification performance – Protocol 2

4. Discussion and conclusions

The work presented so far can be considered as a heuristic survey of the proposed issue: the application of a SVM algorithm for classifying normal and pathological fetuses, based on the analysis of FHR recordings.

The performed trials seem to show how a reduction of the input-output space (the number of ctg parameters taken into account, the gestational age as well as the typology of the discriminated pathologies) resulted in a better classification.

The best percentage of correct classifications was scored presenting a highly filtered training set with only 65 of the starting 909 available records.

Moreover, we found two of the nine parameters deriving from the time domain analysis of CTG tracings (II and STV) less informative and thus eliminable.

Finally, the best improvement was certainly due to a restriction in the possible pathologic conditions that the classifier was meant to learn. The best SVM we built was a mono-pathology classifier, since it performed the dichotomy between healthy and IUGR fetuses.

These results could be extended to other mono-pathology classification issues, training different SVMs for detecting a single unhealthy condition. All these classifiers could then be integrated into a combined identifier containing a module able to merge the binary output of them into a multi-pathologies discriminator.

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