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CLASSIFICATION OF CARDIOTOCOGRAMS USING SUPPORT VECTOR MACHINES

George Georgoulas, Chrysostomos Stylios[1], João Bernardes[2] and Peter Groumpos

Laboratory for Automation & Robotics, University of Patras, 26500, Patras, Greece,
Tel. +30 2610997293 Fax +302160997309 Email: georgoul@ ee.upatras.gr

Computer Science Department, University of Ioannina, 45510 Ioannina, Greece
Tel. +302651098818 Email stylios@cs.uoi.gr

Department of Gynecology and Obstetrics, Porto Faculty of Medicine, Porto, Portugal
Emai: jbernardes@mail.telepac.pt

Abstract: There is an ongoing effort to develop advanced methods and computer based systems to assist the obstetricians in the difficult task of feature extraction and the classification of the Cardiotocogram (CTG), which is the most widely used electronic fetal monitoring method all over the world. In this research work we propose an integrated methodology for CTG analysis and classification. A novel set of features, derived from the time and frequency domains, is used to feed the new powerful tool for pattern classification, named Support Vector Machines (SVMs). Here a new integrated methodology is proposed for signal processing, feature extraction and finally classification of CTG, This methodology is applied to a data set and the achieved overall classification performance is 86.11%.

Keywords: classification, signal analysis, signal processing, support vector machines.

1.INTRODUCTION

The main mean for antepartum and intrapartum fetal surveillance is the Electronic Fetal Monitoring (EFM). The EFM is based on the continuous recording and monitoring of the instantaneous Fetal Heart Rate (FHR) (beats/min) and Uterine Activity (UA), which is also called cardiotocogram (CTG). The typical printout of a CTG consists of the FHR at the upper part and the UA at the lower part for the same time axis (Figure 1). Obstetricians use the CTG during the crucial period of labor to monitor the fetal condition so as to avoid neonatal compromise, namely metabolic acidosis (Geijn, 1996). The medical device that is used for acquiring, processing, displaying and printing out the FHR and UA signals is the cardiotocograph.

Despite the fact that EFM was introduced more than four decades ago, there is still controversy regarding its effectiveness, especially among obstetricians. Another important issue is that statistical studies revealed an increase in operative vaginal deliveries when pregnant women are monitored with EFM during the intrapartum period (McDonald, *et al*., 1985). Furthermore, studies on the FHR analysis and interpretation by obstetricians have shown significant inter-observer and intra-observer variation in tracing interpretation (Bernardes, *et al*., 1997). Even though specific guidelines have been published for FHR interpretation (Rooth, *et al*., 1987; National Institute of Child Health and Human Development Research Planning Workshop, 1997), the different levels of experience of the various specialists, along with the subjectivity of the approach, have great influence on their final judgment. All these facts have created a mistrustful environment for FHR monitoring and interpreting methods.

In addition, the difficulty in distinguishing benign variant patterns from patterns associated with significant fetal acidemia may have arisen because

FHR monitoring was introduced into clinical practice before the physiological mechanism that defines the FHR patterns was well understood (Fox, *et al.*, 2000).

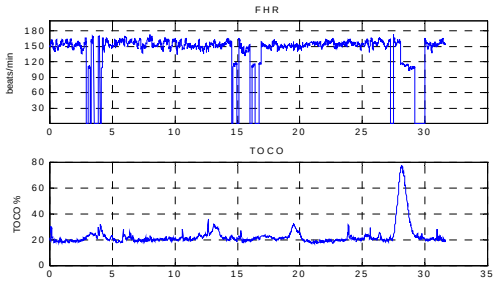

Fig. 1. A simple cardiotocogram (printout) consisting of the FHR at the upper part and UA at the lower part.

On the other hand, there is an ongoing interest for more automated methods for FHR processing and analysis that drives the development of computer based systems able to analyse, classify and intepret the CTG (Arduini, *et al.*, 1993; Berdina, *et al*., 2002; Bernardes, *et al*., 1991; Magenes, *et al*., 2000; Cazares, *et al*., 2001; Chung, *et al*., 1995; Dawes, *et al*., 1995; Jezewski, and Wrobel, 1993; Krause, 1990; Maeda, *et al*., 1990; Mantel, *et al.*, 1990a; Mantel, *et al.*, 1990b; Salamelekis, *et al.*, 2002; Skinner, *et al.*, 1999; Taylor, *et al.*, 2000). These approaches are based on classical signal processing methods, Neural Networks, Fuzzy logic and hybrid methods. Some of these efforts tried to develop a system not to just record the CTG, but actually monitor the condition of the fetus in a reliable, effective and reproducible manner. These research efforts have shown that it is still worth to further investigate methods to analyze the FHR not just by imitating the way a clinician does, but by employing techniques based on the signal processing and pattern recognition fields.

In this research work we introduce the use of a novel classification method, the Support Vector Machines (SVMs), for the classification of FHR and we propose a methodology to process the FHR, extract features and finally classify the FHR based on these features. We implement this method in a data set where fetuses have been divided into two categories, based on the value of their umbilical cord pH. After the processing of FHR, we extract a set of features for each FHR signal that are subsequently fed to a SVM classifier (Burges, 1998). We test different schemes of SVMs and, as it will be shown, the proposed approach, achieves satisfactory performance in classifying FHR.

SVMs have gained great attention and have been used extensively and, most important, successfully in the field of pattern recognition (Burges, 1998; Schokkopf, *et al*., 1999; Veropoulos, *et al*., 1999). Recent findings have shown that using SVMs, it is possible to create reliable classifiers even when the sample size is small (Duin, 2000). Our data sample is indeed small and this was another reason for selecting SVMs as the classifier to be used after the feature extraction stage.

This paper is structured as follows; section 2 briefly introduces the fundamentals of SVMs. Section 3 describes the proposed methodology, the processing steps of the FHR so as to extract the selected features that are used by the SVM classifier. Section 4 presents the implementation and the experimental results in our data set and in section 5 some conclusions and ideas for future work are discussed.

2.SUPPORT VECTOR MACHINES

Support Vector Machines are learning systems that are trained using an algorithm based on optimization theory (Burges, 1998). The aim of a support vector classifier is to "construct" the best separating hyperplane in a high dimensional feature space. By the term "best", it is suggested that it will select the linear separating hyperplane with the maximal margin in this higher dimensional space.

Having a data set $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$ of labelled examples $y_i \in \{-1,1\}$, this can be achieved, in the simple case of linearly separable patterns, by constructing a hyperplane $\mathbf{w}_o \cdot \mathbf{x} + b_o = 0$, where the vector $\mathbf{w}_o$ minimizes $\frac{1}{2}\|\mathbf{w}\|^2$ subject to the constraints

$$y_i((\mathbf{w} \cdot \mathbf{x}_i) + b) \geq 1 \quad i = 1,...,n \tag{1}$$

Because a linear function is often not adequate in real problems to perform this separation, a mapping of the input space into a high dimensional feature space is performed via a non-linear mapping $\boldsymbol{\varphi}(\cdot)$. Therefore, for each training example $\mathbf{x}_i$ we have a new vector $(\boldsymbol{\varphi}(\mathbf{x}_i \cdot))$ in high dimensional space and in order to have perfect classification, the following condition should be satisfied

$$y_i((\mathbf{w} \cdot \phi(\mathbf{x}_i)) + b) \geq 1 \quad i = 1,...,n \tag{2}$$

Still the quantity to be minimized is $\frac{1}{2}\|\mathbf{w}\|^2$.

However, even the mapping into a higher feature space through a nonlinear function does not guarantee that a perfect separation of the classes can be achieved (actually, misclassification of some degree is the rule, not the exception), therefore one introduces slack-variables to relax the hard margin constraints

$$y_i((\mathbf{w} \cdot \phi(\mathbf{x}_i)) + b) \geq 1 - \xi_i \quad \xi_i \geq 0 \quad i = 1,...,n \tag{3}$$

allowing for some misclassifications. The new quantity that has to be minimized is

$$\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \tag{4}$$

The solution to this optimization problem, subject to the constraints (4), is given by the saddle point of the primal Lagrangian:

$$L_p(\mathbf{w},b,\boldsymbol{\xi},\boldsymbol{\alpha},\boldsymbol{\beta}) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{n}\xi_i - \sum_{i=1}^{n}\beta\xi_i - \sum_{i=1}^{n}\alpha_i\left(y_i\left(\mathbf{w}^T\boldsymbol{\varphi}(\mathbf{x}_i)+b\right)-1+\xi_i\right) \quad (5)$$

This leads to the dual maximization problem of the dual Langrangian

$$L_d(\boldsymbol{\alpha}) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j\left(\boldsymbol{\varphi}(\mathbf{x}_i)\cdot\boldsymbol{\varphi}(\mathbf{x}_i)\right) \quad (6)$$

subject to the constraints:

$$\sum_{i=1}^{n}\alpha_i y_i = 0 \text{ and } C \geq \alpha_i \geq 0 \ , \ i = 1,...,n \quad (7)$$

By adjusting C, the user determines the amount of overlapping. This parameter determines the influence of training data points that will remain on the wrong side of a separating nonlinear hypersurface (hyperplane in the feature space). Parameter C can be determined either experimentally, using a training-validation procedure, or analytically, via the estimation of the Vapnick-Chervonenkis (VC) dimension (Haykin, 1999).

Another important issue is that by choosing a proper (symmetric) kernel function (Burges, 1998), one can avoid the direct computation of the inner product $\boldsymbol{\varphi}(\mathbf{x}_i)\cdot\boldsymbol{\varphi}(\mathbf{x}_i)$ in the feature space and perform it in the input space $\boldsymbol{\varphi}(\mathbf{x}_i)\cdot\boldsymbol{\varphi}(\mathbf{x}_i) = K(\mathbf{x}_i,\mathbf{x}_j)$. Therefore, by selecting an appropriate symmetric kernel function, one does not even have to know what is the actual mapping and, furthermore, the computational complexity is reduced. Depending on the choice of the kernel function, different learning machines with different nonlinear decision surfaces can be constructed. Among others, the most popular are the polynomial learning machines, the radial basis function networks and the two-layer perceptrons. In our experimental procedure we only employ radial basis function machines. In this case the inner product kernel is:

$$K(\mathbf{x},\mathbf{x}_i) = \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{x}-\mathbf{x}_i\|^2\right) \quad (8)$$

where the width σ^2 is specified a priori by the user and is common for all the kernels.

3.PROCESSING OF FHR FOR FEATURE EXTRACTION

3.1 Pre-processing and Artifact Removal

The FHR is a noisy signal due to the method that is used for its acquisition and also due to extraneous interferences that cannot be isolated. Although the missing or "spiky" parts do not provoke serious problems to simple eye inspection and interpretation, they may lead to wrong results when digital processing is applied to FHR. Therefore, it is necessary to remove the "spiky" segments or segments where the signal is zeroed; and for this purpose, a pre-processing stage of the FHR signal has to take place. The pre-processing stage, introduced in (Bernardes, *et al.*, 1991), firstly detects a stable FHR segment, which is defined as a segment where the difference (in beats/min) between five adjacent samples is less than 10 beats/min. Whenever a difference between adjacent beats higher than 25 beats/min is found, a linear interpolation is applied between the first of those two signals and the first signal of a new stable FHR segment) (Figure 2).

In this work, the data set consists of 36 recordings. The recordings have various lengths, varying from 20 minutes to more than 1 hour. Thirty of them were acquired using a HP 1350 fetal monitor at a sampling frequency of 4 Hz and 6 of them were acquired using a Toitu MT810B. The latter FHRs were irregularly sampled and we transformed them into "pseudo-regularly" sampled signals by implementing a virtual sample and hold procedure (Georgoulas, *et al.*, 2003) (with a frequency of 4 Hz). All tracings were acquired using a scalp electrode (Carter, 1991) until the very vaginal delivery or until the very beginning of a caesarean section (i.e. no more than 30 minutes before a caesarean delivery) thus avoiding time-bias.

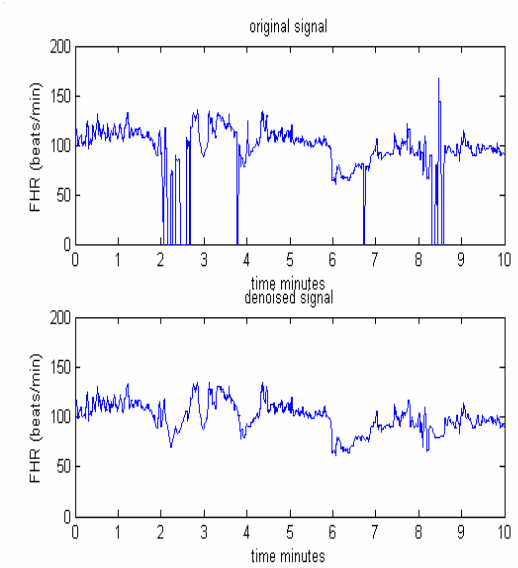

Fig.2. Data before and after the removal of artifacts.

For consistency related reasons we use segments of equal duration from each case. We tried 3 different

segmentations. We cropped, starting from the end of the recording (or as close to the end as possible), segments lasting 5, 10 and 20 minutes (maximum duration of some recordings). Due to the stress during the last stage of delivery the 1-3 last minutes of the recording were completely "contaminated" by artifacts and we excluded them from our data set.

3.2 Feature Extraction

As mentioned above, we had 3 different segment durations, meaning that we performed 3 different sets of experiments. For each one of the sets we employed a feature extraction stage in order to find a group of indexes that can characterize fetal condition. Those indexes -features- were derived from both the time domain (following (Magenes *et al.*, 2000) and the frequency domain of FHR.

The first features are 7 parameters calculated in the time domain. The set of parameters and their definitions are given bellow.

- Mean value of FHR signal
- Standard deviation of FHR signal
- $\text{Delta}=\dfrac{\sum_{\text{i=1}}^{\text{m}}\left[\max\left(FHR(i)\right)_{i\in m}-\min\left(FHR(i)\right)_{i\in m}\right]}{m}$
  where max and min are computed within each minute of the signal and m is the number of minutes
- $STV=\dfrac{\sum_{i=1}^{24}\left|sFHR(i+1)-sFHR(i)\right|}{24}$, where $sFHR(i)$ is the value of the signal $FHR(i)$ taken each 2.5 sec (i.e. once each 10 samples) (Short Term Variability)
- $II=\dfrac{STV}{std\left[sFHR(i)\right]}$ (Interval Index)
- LTI is defined as the interquartile range $\left[\frac{1}{4},\frac{3}{4}\right]$ of the distribution $m(j)$ with $m(j)=\sqrt{FHR^2(j)+FHR^2(j+1)}$ (Long Term Irregularity)
- $\text{Delta\_total}=\max\left(\text{FHR(i)}\right)-\max\left(\text{FHR(i)}\right)$

In addition to them, we also extracted 4 simple "features" from the frequency domain.

- Power at the range 0-0.5 Hz
- Power at the range 0.5-1 Hz
- Power at the range 1-1.5 Hz
- Power at the range 1.5-2 Hz

The above time domain parameters were successfully used in the anteparum case (Magenes *et al.*, 2000), therefore it was reasonable to assume that they may also perform well in the intrapartum case. Regarding the frequency domain, what has been used till now, is the frequency content of FHR variability (Magenes, *et al.*, 2000). Therefore, the selection of the frequency bands was done arbitrarily.

Our proposed methodology suggests after extracting the 11 parameters-features for each FHR, to proceed to the next stage, where the classification of each recording FHR is performed, based on these extracted features using SVMs. Here the SVMs with radial basis function kernels are utilized.

4. CLASSIFICATION

The extracted features from the FHR signal were fed to a SVM classifier so as to test whether we can find a way to discriminate between fetuses with "normal" pH values and those who have a decreased pH and are suspicious of developing acidemia. For the needs of this work we chose a cut-off value of pH=7.05 as the borderline (threshold) between hypoxic and normal cases. With this convention, the 36 recordings were divided into two groups: the "normal" group, containing 20 cases, and the "hypoxic" group with 16 cases.

Because of the restricted number of cases, we decided to use the multifold cross validation scheme (Haykin, 1999) in order to evaluate the performance of the proposed methodology. That was, we divided the 36 cases into 4 non-overlapping groups containing 9 cases each (5 normal and 4 hypoxic). Each time we excluded one of them from the training process and we used it only for testing the performance of the constructed SVM classifier. We repeated this procedure 4 times and we averaged the classification performances.

The SVM that we used was based on radial basis function kernels and we experimented with different values for the width parameter σ^2 and also the parameter that controls the overlap (C). In order to find the best values for the two parameters, we tested various configurations and combinations of them in a systematic manner, which can be described as a grid search. Figure 3, shows the overall classification performance is and how this procedure is affected by the change of C and σ^2.

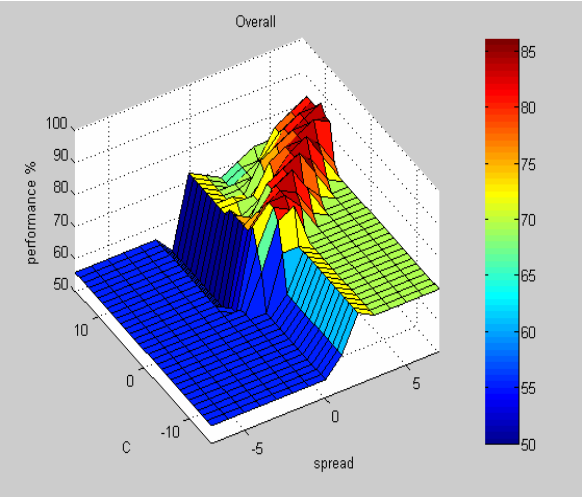

Fig.3. Overall performance of our classifier for the case of 20 minute segments for different values of σ^2 and C.

In Table 1, the best performance for the 3 different time divisions is shown. The best performance was achieved for similar configurations of the SVM classifier

Table 1. Best classification performance for the 3 different time segments

	Overall Performance	Normal cases	"Abnormal" cases
20 min	86.11 %	95 %	75%
10 min	86.11 %	90%	81.25
5 min	86.11 %	90%	81.25

5.CONCLUSIONS

The overall tests showed that the proposed classification methodology has satisfactory results for both classes. The results are more satisfactory compared to previous studies where SVMs and Independent Components Analysis were used for feature extraction and classification respectively (Georgoulas, *et al.*, 2003) in the same data set. Moreover, the increased classification performance for the hypoxic cases when we had time segments of 5 and 10 minutes, compared to the longer 20 minute segments, indicates that the final minutes of a delivery process are those that affect more the value of the pH. This is something acknowledged by obstetricians. Therefore, it would be helpful, and it is something that we are considering, to propose a method to trace and indicate when a fetus is passing from a "healthy" condition (normal pH) to a distressed one (acidemia) based on the FHR tracing.

However, the choice of the threshold for the pH value, perhaps should be chosen lower for the 'hypoxic'' case. A more justified threshold could be the value of pH at 7, but this could compromise more the classification performance, since only 2 cases would fulfil that criterion, leaving 34 to the normal set. It is obvious that with this partition, over-fitting would occur. It must be mentioned that only very low pH values (6.8) are related to neonatal death or major neurological damage (Parer, 1997).

In view of all the above discussion, we are planning to test the proposed method on a larger set of data to further validate it. Furthermore, we also intend to include in the feature set some morphological features of FHR, such as the accelerations and decelerations etc, so as to examine the influence that they might have to the outcome of the classification.

In the future, we will also consider the use the fetal Apgar score as another index component for the formation of the classes, something which was not used in this work, since all Apgar scores but one were higher than 8. By including the Apgar score in the classification process, a more objective categorization may be achieved (Bernardes, *et al.*, 1998)

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REFERENCES

Arduini, D., G. Rizzo, G. Piana, A. Bonalumi, P. Brambilla and C. Romanini (1993). Computerized Analysis of Fetal Heart Rate: I. Description of the System (2CTG). *J. Maternal Fetal Invest.*, **vol. 3**, pp. 159-163.

Berdinas, B. G., A. A. Betanzos and O. F. Romero (2002). Intelligent analysis and pattern recognition in cardiotocographic signals using a tightly coupled hybrid system. *Artificial Intelligence*, **vol. 136**, pp. 1-27.

Bernardes, J., C. Moura, J.P.M. de Sa and L.P. Leite (1991). The Porto system for automated cardiotocographic signal analysis. *J. Perinat. Med.*, **vol. 19**, pp. 61-65.

Bernardes, J., A. C. Pereira D. A. de Campos, H. P. Van Geijn, L.P. Leite (1997). Evaluation of interobserver agreement of cardiotocograms. *Int J Gynecol Obst* **vol. 57,** no. 1, pp.33-37.

Bernardes, J., D. A. de Campos, A. C. Pereira, L.P. Leite and A. Garrido (1998). Objective computerized fetal heart rate analysis. *Int. J. Gynecol. Obst.*,**vol. 62**, pp. 141-147.

Burges, C. J. C. (1998). A Tutorial on Support Vector Machines for Pattern Recognition. *Data mining and Knowledge Dicovery*, **vol. 2**, pp. 121-167.

Carter, M. C., (1991). Present-day performance qualities of cardiotocographs. *Br. J. Obstet.*

Gynaecol., **vol. 100**, Supplement 9, pp. 454-460.

Cazares, S., M. Moulden, C.W.G. Redman and L. Tarasenko (2001). Tracing poles with as autoregressive model: a confidence index for the analysis of the itrapartum cardiotocogram. *Medical Engineering & Physics*, **vol 23**, pp. 603-614.

Chung, T. K. H., M. P. Mohajer, X. J. Yang, A. M. Z. Chang and D.S. Sahota (1995). The prediction of fetal acidosis at birth by computerized analysis of intrapartum cardiotocography. *Br. J. Obstet. Gynaecol.*, **vol. 102**, pp. 454-460.

Dawes, G. S., M. Moulden, and C. W. Redman (1995). Computerized analysis of antepartum fetal heart rate. *Amer. J. Obstet. Gynecol.*, **vol. 173**, no. 4, pp. 1353-1354.

Donker, D. K., H. P. Van Geijn and A. Hasman (1993). Interobserver variation in the assessment of fetal heart rate recordings. *European Journal of Obstetricy Gynaecology and Reproductive Gynecology*, **vol. 52**, pp. 21-28.

Duin R.P.W. (2000). Classifiers in almost empty spaces. In Proceedings of the 15th International Conference on Pattern Recognition, Barcelona, September 3-8, **vol 2**, pp. 1-7.

Fox, M., S. Kilpatrick, T. King and J. T. Parer (2000). Fetal heart rate monitoring: Interpretation and collaborative management. *Journal of Midwifery & Women's Health*, **vol 45**, no 6, pp. 498:507.

Geijn, H. P. V. (1996). Developments in CTG analysis. *Bailliers Clin. Obstet. Gynaecol.*, **vol. 10**, no 2, pp. 185-209.

Georgoulas, G., C. Stylios and P. P. Groumpos (2003). Integrated Approach for Classification of Cardiotocograms based on Independent Component Analysis and Neural Networks. *Proceeding of 11th IEEE Mediterranean conference on Control and Automation*, June 18-20, Rodos, Greece.

Haykin, S. (1999). *Neural Networks: A Comprehensive Foundation*. 2nd ed. Englewoo Cliffs, NJ, Prentice Hall.

Jezewski J. and J Wrobel (1993). Foetal monitoring with automated analysis of cardiotocogram: The KOMPOR system. in Proc. *15th Ann. Card. IEEE/EMBS*, San Diego, CA, pp. 638-639.

Krause, W. (1990). A computer aided monitoring system for supervision of labour. In: *Computers in perinatal medicine* (K. Maeda (Ed)), pp. 103-111. Elsevier Science Publishers, Amsterdam, The Netherlands.

McDonald, D., A. Grant, M. Sheridan-Pereira, P. Boylan and I. Chalmers (1985). The Dublin randomized controlled trial of intrapartum fetal heart rate monitoring. *Am. J. Obstet Gynecol.* **vol. 152**, pp. 524-39.

Maeda, K. (1990). Computerized analysis of cardiotocograms and fetal movements. *Bailliers Clin. Obstet. Gynaecol.*, **vol. 4**, no. 4, pp. 1797-813.

Magenes, G., M.G Signorini and D. Arduini (2000). Classification of cardiotocographic records by neural networks. *D.* Neural Networks,. In Proceedings of the IEEE-INNS-ENNS International Joint Conference **vol** 3 pp. 637-641.

Mantel, R., H.P. van Geijn, F.J.M Caron, J. M. Swartjes, E. E. van Woerden and H. W. Jongsma (1990a). Computer analysis of antepartum fetal heart rate: 1. Baseline determination. *Int. J. Biomed. Comput.*, **vol. 25**, no. 2, pp. 261-272.

Mantel, R., H.P. van Geijn, F.J.M Caron, J. M. Swartjes, E. E. van Woerden and H. W. Jongsma (1990b). Computer analysis of antepartum fetal heart rate: 2. Detection of accelerations and decelerations. *Int. J. Biomed. Comput.*, **vol. 25**, no. 2, pp. 273-286.

National Institute of Child Health and Human Development Research Planning Workshop. (1997). Electronic fetal heart rate monitoring: Research guidelines for interpretation. *Am. J. Obstet Gynecol*. **vol. 177**, pp. 1385-90.

Parer, J. T. (1997). *Handbook of fetal heart rate monitoring*. Philadelphia, Pennsylvania: W. B. Saunders Company.

Rooth, G., A. Huch and H. Hough (1987). Guidelines for the use of fetal monitoring. *Int. J. Gynecol. Obstet,*.**vol 25** pp. 159-67.

Salamalekis, E., P. Thomopoulos, D. Giannaris, I. Salloum, G. Vasios, A. Prentza and D. Koutsouris (2002). Computerised intrapartum diagnosis of fetal hypoxia based on fetal heart rate monitoring and fetal pulse oximetry recordings utilising wavelet analysis and neural networks. *British Journal of Obstetrics and Gynaecology*, **vol. 109**, no. 10, pp. 1137-1142.

Schokkopf, B., C.J.C. Burges and A.J Smola (1999). *Advances in Kernel Methods. Support Vector Learning*. The MIT Press, London.

Skinner, J. F., J. M. Garibaldi and E. C. Ifeachor, (1999). A Fuzzy System for Fetal Heart Rate Assessment. I*n Proc of the 6th Fuzzy Days Conference*, Dortmund, Germany, pp. 20-29.

Taylor, G. M., G. J. Mires, E. W. Abel, S. Tsantis, T. Farrell, P. F. W. Chien and Y. Liu (2000). The development and validation of an algorithm for real time computerized fetal heart rate monitoring in labour. *Br. J. Obstet. Gynaecol.*, **vol, 107**, pp. 1130-1137.

Veropoulos, K., Cristianini, C. Campbell (1999). The Application of Support Vector Machines to Medical Decision Support: A Case Study. Proceedings of the ECCAI Advanced Course in Artificial Intelligence.