CLASSIFICATION OF FETAL HEART RATE TRACINGS BASED ON WAVELET-TRANSFORM & SELF-ORGANIZING-MAP NEURAL NETWORKS

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Abstract-**The objective of the present study is the development of an automated computerized system that will assist the early diagnosis of fetal hypoxia. We demonstrate that it is possible to distinguish between healthy subjects and acidemic fetuses by way of wavelet transform analysis of the fetal heart rate recordings and fetal pulse oximetry ($FSpO_2$). We focus on the values of the standard deviation of the wavelet components (up to scale index 5) and we apply Self-Organizing-Map in order to investigate the relationship between the fetal heart rate variability in different scales and $FSpO_2$ (taking as a threshold for the $FSpO_2$, the 30% level and considering the minimum value of $FSpO_2$ during a 10-minute segment) for normal and acidemic fetuses during the second stage of labor, which can be used to discriminate acidemic fetuses from normal ones. A total accuracy of 91% has been achieved, enabling us to correctly classify all the normal cases (but one) as belonging in the normal group and all pathologic cases (but two) as belonging in the acidemia group, therefore providing a clinically significant measure for the discrimination of the different groups. Fetal pulse oximetry seems to be an important additional source of information.**

***Keywords* – Fetal heart rate monitoring, fetal pulse oximetry, fetal hypoxia, wavelet analysis, neural network**

I. INTRODUCTION

During the last decades, fetal heart rate (FHR) monitoring has been widely used for intra- and antepartum monitoring and assessment of fetal well-being. It is commonly used as a screening modulus of the fetes to detect in advance possible fetal problems that could result in irreversible neurological damage or even fetal death during labor. Although it has been proved to be a useful tool for the obstetricians, suspicious FHR patterns lack specificity and false positive FHR traces may result in unnecessary intervention increasing the caesarian section delivery rate. More recently, non-invasive techniques such as reflectance pulse oximetry with continuous recording of functional oxygen saturation of fetal arterial blood during active labor appear to develop into an important additional source of information about fetal status, especially in cases of non-reassuring fetal heart rate patterns.

In recent years, several attempts have been made to automate the diagnosis of the fetal status. Computerized algorithms, artificial neural networks and hybrid architectures have been developed and validated in order to assess the fetal heart rate parameters (baseline of the fetal heart rate, accelerations and decelerations, etc.). Our method is based on the Heart Rate Variability (HRV) analysis and on the statistical analysis of fetal pulse oximetry ($FSpO_2$).

It has been evident that there is a significant relationship between the autonomic nervous system and cardiovascular mortality even before birth [1]. The development of quantitative markers of the autonomic activity has been encouraged by experimental evidence and HRV represents one of the most promising such markers. Many commercial devices now provide automated measurement of HRV, providing the physician with a seemingly simple tool for both research and clinical studies.

The clinical relevance of HRV was first appreciated in 1965 when Hon and Lee [2] noted that fetal distress was preceded by alterations in interbeat intervals before any appreciable change occurred in the heart rate itself. Later on, Sayers and others focused their attention on the existence of physiological rhythms embedded in the beat-to-beat heart rate signal [3-6]. In 1981, Akselrod et al. [7] introduced power spectral analysis of heart rate fluctuations using Fast-Fourier Transform (FFT) and pointed out the relation between the activities of the autonomic nervous system and the low-frequency (LF) and high-frequency (HF) peaks of the frequency domains. Since then, frequency analysis of heart rate fluctuation has been performed widely [8] and applications to fetal distress have been attempted [9-12]. Most of these studies are based on the application of FFT and Autoregressive Modeling (AR). However these algorithms have limitations in the study of long-term non-linear variations of heart rate as well as in the analysis of transient alterations of heart rate. Since the fetal heart rate shows a long-term nonstationary behavior [13], the application of the above methods is not very effective. Wavelet analysis [14-20] has proved to be one of the most successful techniques for the analysis of signals at multiple scales, even when nonstationarities are present, which often obscure such signals [21-22] and has rendered many successful applications in the area of biomedical signal processing [23-24]. Ivanov et al. [25] used wavelet transform (WT) to study the temporal fluctuation of the high frequency component of the heart rate fluctuation. Later, Thurner et al. [26] used a similar procedure and focused on the values of the wavelet coefficients variance rather than on the scaling exponent of the WT.

Continuous electronic fetal monitoring (EFM) was incorporated in clinical obstetrics in the late 1960s. It still remains the accepted method of intrapartum fetal monitoring in high-risk pregnancies. However, debate is still unsettled regarding the benefits of EFM as opposed to intermittent auscultation in labor. Prospective studies in both term and preterm infants have consistently failed to show lower rates

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle CLASSIFICATION OF FETAL HEART RATE TRACINGS BASED ON WAVELET-TRANSFORM & SELF-ORGANIZING-MAP NEURAL NETWORKS	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) 1 Biomedical Engineering Lab., Dept. of Electrical & Computer Engineering, National Technical University of Athens, Greece	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
4

of perinatal mortality and morbidity in labors monitored by EFM as compared with those monitored by intermittent fetal heart rate auscultation. Furthermore, suspicious FHR patterns lack specificity and false positive FHR traces may engender unnecessary intervention. Meta-analyses of the trials of the use of intrapartum EFM versus intermittent auscultation show that EFM, with or without adjunctive fetal acid-base assessment, is associated with a significant increase in caesarean delivery and instrumental vaginal delivery of fetal distress. This increase in operative delivery is not associated with improved neonatal morbidity or mortality, except in labors associated with the use of oxytocin and in prolonged labor, where there were more infants with neonatal seizures in the intermittent auscultation group compared with the more intensively monitored group. The cost effectiveness and possibility of increasing the caesarean delivery rate without any substantial fetal benefits leads one to question the use of EFM in low risk labor [27].

There is evidently a need to improve intrapartum fetal surveillance. The ideal system of fetal monitoring, one that is safe, direct, continuous and non-invasive, with acceptable sensitivity and specificity has yet to be determined. Pulse oximetry has been used extensively in the fields of neonatology, adult intensive care and anesthesia. Considering its successful application in these fields, it would seem logical to extend its use in the area of intrapartum fetal surveillance. Much research has gone into evaluating fetal pulse oximetry, its safety, accuracy and reliability in predicting neonatal outcome. There have been several studies conducted correlating the fetal heart rate patterns and the $FSpO_2$ [28].

In this study, we use the WT of the fetal HRV and we apply Self-Organizing-Map (SOM) in order to investigate the relationship between the fetal HRV in different scales and $FSpO_2$ (taking as a threshold value for the $FSpO_2$ measurement the 30% level and calculating the distance between the threshold and the minimum value of $FSpO_2$ during a 10-minute segment) for normal and acidemic fetuses during the second stage of labor, which can be used to discriminate acidemic fetuses from normal ones. Our system accepts as inputs the fetal heart rate recording and the $FSpO_2$ measurements. Pre-processing and artifact elimination takes place. Wavelet analysis is applied on 10-min fetal heart rate segments and certain parameters (standard variation of the wavelet coefficients) are estimated, which together with the $FSpO_2$ measurements comprise the inputs to the SOM neural network. The flow chart of the analysis is shown in Fig. 1.

II. Methodology

A. Data Collection

Data were collected from thirty-five (35) women during labor, which took place in the Labor Ward of the 2nd University Clinic of Obstetrics and Gynecology at Aretaieion Hospital of Athens. All women gave informed consent to this study. Twelve (12) cases, in which pH was lower than 7.2 and Apgar score < 9 were grouped together in the risk group. The rest of the women formed the normal group. The Cardiotocogram (CTG) and the $FSpO_2$ have been recorded during labor using the Corometrics Series 120 Cardiotocograph combined with fetal pulse oximeter. The duration of the second stage of the labor ranged from 20 to 50 minutes.

The fetal heart rate is measured externally. A transducer placed on the mother's abdomen is used to direct an ultrasonic beam toward the fetal heart and to sense Doppler shifted echoes created by moving cardiac structures. The sampling frequency was 1 Hz.

The percentage of the functional oxygen saturation of fetal arterial blood ($FSpO_2$) is measured non-invasively by applying the Nellcor Puritan Benett (NPB) fetal oxygen sensor to the cheek/temple area of the fetal head.

B. Pre-processing Stage

The active (second) stage of each case was divided into 10-minute segments (600 values of FHR). Artifacts have been removed from both the FHR signal and the $FSpO_2$. Abrupt changes of $FSpO_2$ were removed and linear interpolation was employed, when the duration of the artifact was below a certain value.

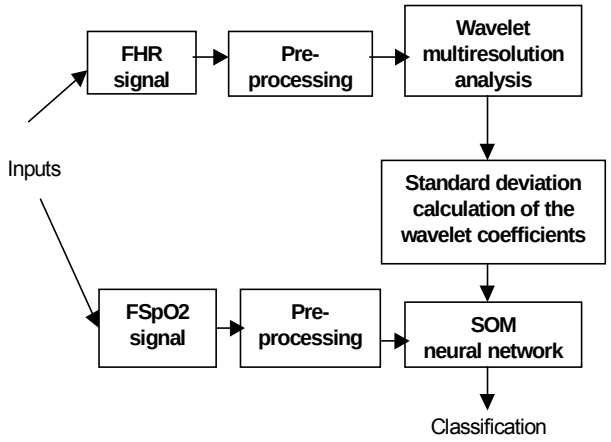

Fig. 1. Flow chart of the analysis.

C. Wavelet Based Analysis

We applied wavelet multiresolution analysis for each 10-minute segment in order to address the problem of long-term nonstationary behavior of the fetal heart rate tracings and to estimate the power in different frequency ranges. The multi-scale feature of the wavelet transform allows the decomposition of a signal in to a number of scales, each scale representing a particular 'coarseness' of the signal under study [15]. This essentially decomposes the signal into a set of signals of varying 'coarseness' ranging from low frequency components progressively to high frequency components. Thus, if one can make some decision concerning the underlying frequency components of the signal, one may choose the appropriate scale in the wavelet transform, whilst ignoring the contribution of the other

scales. This decomposition of the signal into different scales is particularly useful if the wavelet transform is performed on an orthogonal basis.

The used mother wavelet was Daubechies 20 – tap. The decomposition was performed up to scale index 5. For each scale, we have calculated the wavelet coefficient standard deviation $\sigma_{wav}(i)$, where i is the scale index. $\sigma_{wav}(1)$ and $\sigma_{wav}(2)$ were excluded from further analysis, because we haven't noticed any significant difference between normal and acidemic groups. $\sigma_{wav}(5)$ was excluded from further analysis, because according to Ze-Yan Yu et al. [29], there is uncertainty as to the physiological significance of changes in power in the corresponding frequency range, and we also wanted to focus on the power that corresponds to the 3rd an 4th scale of analysis (associated frequencies 0,08 and 0,04 Hz respectively).

D. Statistical Analysis of $FSpO_2$

For each 10-minute segment we calculated the percentage of time in which the $FSpO_2$ was less than 30% ($SpO2_{30}$).

We also calculated the distance between the lowest value of $FSpO_2$ in the 10-minute segment and the 30% threshold (dist(30-min$FSpO_2$)).

E. Classification using SOM Neural Networks

In order to categorize the different 10-minute fetal heart rate patterns, we used the Self-Organizing Map (SOM) neural network with the Kohonen learning rule [30]. Such a network consists of two layers: an input layer and a two-dimensional output, Kohonen layer. Self-organizing maps, also called topology-preserving maps, assume a topological structure among the cluster units. They learn to recognize groups of similar input vectors, in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. During the self-organization process, the cluster unit whose weight vector matches the input pattern most closely (typically, the square of the minimum Euclidean distance) is chosen as the winner. The winning unit and its neighboring units (in terms of the topology of the cluster units) update their weights. In this way, a mapping process takes place; input data vectors with similar features are mapped into the same area of the SOM.

The input vectors are the following: $\sigma_{wav}(3)$, $\sigma_{wav}(4)$, $SpO2_{30}$ and dist(30-min$FSpO_2$). After training the self-organizing neural network, we calculated the U-matrix, which shows the distance between neighborhood units as well as the median distance from each map unit to its neighbors, and the corresponding projection matrices.

III. Results

Fig. 2 visualizes the U-matrix and the projection matrices of the input parameters $\sigma_{wav}(3)$, $\sigma_{wav}(4)$, $SpO2_{30}$ and dist(30-min$FSpO_2$). As we can see in the figure, the lower right part of the U-matrix is separated from the rest and in this area $FSpO_2$ is very low. We can also observe that the percentage of time in which the $FSpO_2$ was less than 30% is high in this area. The same holds for the distance between the minimum $FSpO_2$ value and the 30% threshold (the above can be also observed from the corresponding projection matrices).

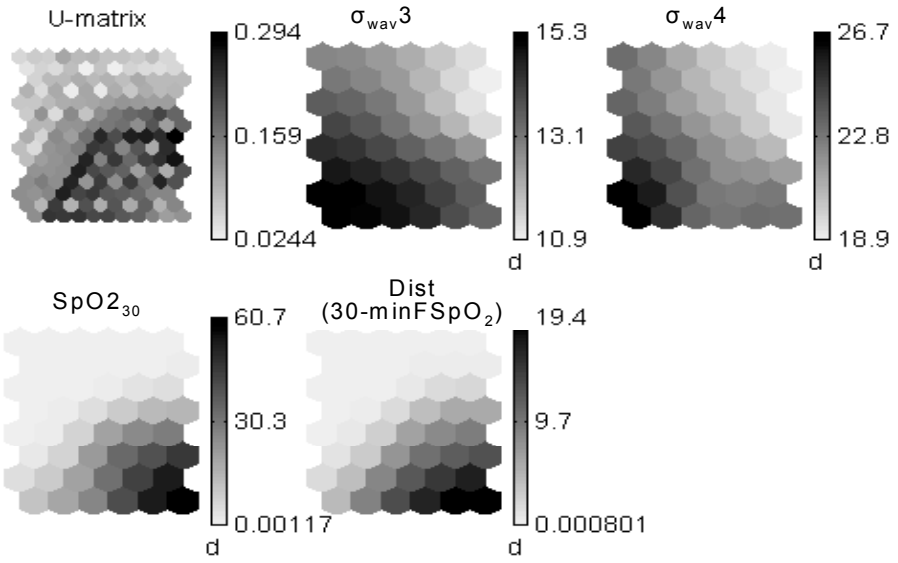

Fig. 2. Visualization of the U-matrix (top left) and the projection matrices of the input parameters.

$\sigma_{wav}(3)$ remains in high levels (lower left corner of its correspondent projection matrix) in the area where $FSpO_2$ is low, while $\sigma_{wav}(4)$ which corresponds to the power of 0,04 Hz diminishes faster.

Fetal pulse oximetry is very important for the classification of the fetal heart rate recordings and the consideration of the distance between the minimum $FSpO_2$ value and the 30% threshold as an input to the neural network enhances the accuracy results.

10-minute segments of ten (10) cases that they have low pH (<7.2) and low Apgar score are included in this area and only one 10-minute segment of a normal case is also included (being though only in close to the borderline).

In order to characterize the performance of the neural network, the sensitivity (SE), specificity (SP), and accuracy (A) were calculated and their values are the following:

SE = 83%, SP = 96%, A = 91%

IV. Discussion & conclusion

We have applied wavelet analysis, since it addresses the problem of long-term nonstationary behavior of fetal heart rate. The calculation of the standard deviation of the wavelet coefficients enables us to extract information about the power in the different scale levels from the fetal heart rate recordings, which in combination with the fetal pulse oximetry is used as input to the SOM neural networks for the categorization of the fetal heart rate patterns.

Fetal pulse oximetry seems to be an important additional source of information. Not only the time in which the $FSpO_2$ was less than 30%, but also the minimum value that $FSpO_2$ reaches play an important role in the classification of the patterns, especially in the cases of non-reassuring fetal heart rate patterns.

We believe that computerized analysis of the fetal heart rate monitoring and pulse oximetry recordings based on the combination of wavelet analysis and artificial neural networks is a very promising technique in objective intrapartum diagnosis of fetal hypoxia. Further evaluation of this technique is mandatory to evaluate its efficacy and reliability in interpreting fetal heart rate records.

Acknowledgment

This work has been supported by the program PENED, Gneral Secretariat of Research and Technology.

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