A Multi-Resolution Principal Component Analysis Neural Network for the Detection of Foetal Heart Rate Patterns

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ABSTRACT: The analysis of the Fetal Heart Rate (FHR) signal is a method for the assessment and prediction of fetal status and is based on the interpretation of certain patterns detected in the FHR. In order to be operative, any automatic system developed for this detection will need to perform in real time. This paper describes an artificial neural network used to recognise accelerative and decelerative patterns present in the FHR. The neural system implements a variation of standard Principal Component Analysis (PCA), a multi-resolution PCA (MR-PCA). The MR-PCA network is constructed in such a way as to provide different visions of the signal at the same time during the components extraction process. This MR-PCA network is followed up by a post-process algorithmic module performing the detection task based on combinations of the components extracted from the FHR. The results of the performance of the overall system are presented and compared (using real patient records) to those obtained by a network using the classical PCA method plus a multilayer perceptron (MLP) for the classification task.

KEYWORDS: Multi Resolution Principal Component Analysis Learning, Sanger´s Rule, Adaptive Signal Analysis, Real-Time Pattern Detection, Fetal Heart Rate Analysis, Intelligent Fetal Monitoring, Hybrid Systems.

BACKGROUND

The evaluation of the intrauterine condition is a standard of care in clinical obstetrics. Among the methods employed for fetal assessment, those based on the testing of the fetal heart rate (FHR) are the most common; and of these, one of the most popular, due to its simplicity and reliability, is the non-stress test (NST). This is based on the relationship between certain FHR patterns and current and predictive fetal status. In performing this test, clinicians analyse the FHR signal in order to extract the parameters on which to base a diagnosis. Specifically, these parameters (Parer (1997)) (Figure 1) are as follows:

- Baseline, calculated as the mean FHR but excluding accelerations, decelerations, and periods of increased FHR variability. In addition, this baseline calculation will have to reflect changes in semantic classification over time.
- Variability, defined as the standard deviation of fluctuations in the FHR baseline.
- The number of accelerations, where an acceleration is defined as an abrupt increase in FHR over the baseline of at least 15 beats/minute in amplitude and of no more than 2 minutes in duration.
- The number and type of decelerations, with a deceleration defined as an abrupt decrease below FHR baseline with the same characteristics of amplitude and duration as accelerations.

In order to be operative, any automatic system for the analysis of the FHR will have to perform both calculations and pattern detection in real time, since the FHR may indicate a critical situation that requires immediate clinical action. Most of the attempts to automate this analysis approach the problem from a classical algorithmic point of view (Lichten (1986), Searle (1988), Dawes (1991), Mantel (1993)) which however, pose certain problems and limitations (Guijarro-Berdiñas (1998B)). Nevertheless, in recent years, new attempts to solve this problem using AI techniques have been made (Paulo-Reis (1994), Keith (1994), Ulbritch (1998), Alonso-Betanzos (1998), Guijarro-Berdiñas (1998A), Guijarro-Berdiñas (1998B)).

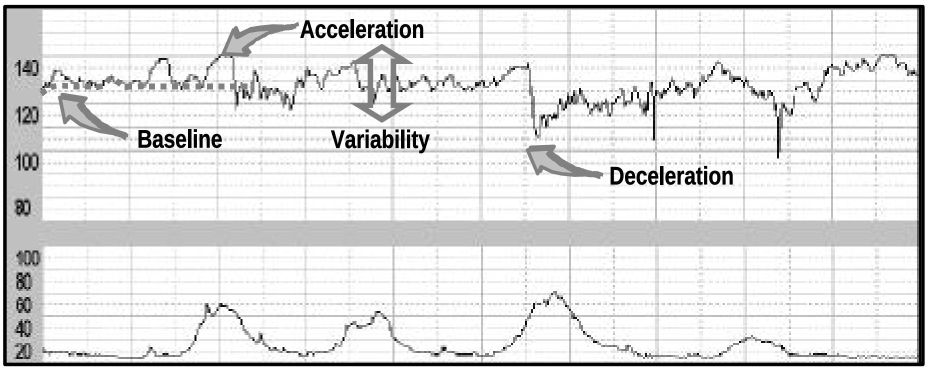

Figure 1: Parameters of the FHR to be analysed.

The authors have recently been working on two approaches to the problem.
The first one is the CAFE hybrid system (Guijarro-Berdiñas (1998A), Guijarro-Berdiñas (1998B)) in which an algorithm calculates in real time, the baseline and variability of the signal and on this basis, the system performs the detection of fetal patterns, accelerations and decelerations. Although fuzzy thresholds have been taken into account in the algorithm, there are still some problems with this approach (as in many other algorithmic approaches). Furthermore, pattern detection is extremely dependent on the baseline calculated in the pattern limits. This baseline evolves with time and is affected by both long- and short-term variability, so it is necessary to establish a balance between a long-term baseline and a more local one for the patterns to be correctly detected. Using an algorithmic solution makes it difficult to obtain a real-time adaptation to the baseline without, at the same time, the algorithm being oversensitive to insignificant changes in the signal. Most of the false positive and false negative patterns detected are due to a failure in the baseline to adapt when using the algorithmic solution.
The second approach consists of a neural system trained for the detection of patterns in such a way as to allow greater flexibility in a real time system to continuously follow the baseline (Alonso-Betanzos (1998)). Two subnetworks make up this system. The first one is an unsupervised network that performs a standard Principal Component Analysis (PCA) on the original signal. Subsequently, certain selected components are provided to a second network, a multilayer perceptron (MLP) with a time delay line in its input layer (TDL) (Haykin (1994)), which is trained to detect accelerative and decelerative patterns. The use of principal components in the place of the raw FHR signal as input to the MLP has two advantages. Firstly, redundant components in the signal together with components that contribute least to variations in the data set are eliminated. Secondly, only those components that are relevant to the identification of FHR accelerations (or decelerations) will be fed to the MLP, thus making the detection task easier. Finally, the component corresponding to the baseline of the FHR will always be eliminated; thus overcoming all the problems derived from variations in the baseline during the detection process.
Although many of the false positives and false negatives occurring as a consequence of the failure of the algorithmic system to adapt to the baseline, were accurately detected by this neural system, there is still the problem of the tendency to detect false positives at the end of patterns of long duration. These false positives are a result of the time delay line in the input to the MLP being insufficient to cope with the duration of those patterns, and so it interprets the end of an acceleration as the beginning of a deceleration and vice versa. However, an increment in the tap delay line did not improve the results obtained, since it also increased the number of weights in the network considerably.
In this paper, a new approximation based on a multi-resolution PCA (MR-PCA) network is presented.

DESCRIPTION OF THE NEURAL SYSTEM

In the complete detection system two very distinct parts can be identified. The first part of the system is a neural network that performs MR-PCA (Brennan (1998)). It is well known that an alternative solution to PCA can be found in a linear system that utilises adaptive algorithms. In this case, Sanger´s Rule (Sanger (1989)) has been used to train a network with no hidden layers in an unsupervised mode to obtain the principal components of the FHR signal. To provide the network with dynamic characteristics, a time delay line restricted to the input layer was used.

The novelty with respect to the classical PCA method comes from the connections between the input and the output layer. In this case, as can be seen in Figure 2, instead of a full connection between all the elements in both layers, each set of n output elements will be provided only with the first $1/2^i$ elements from the input TDL, where $i = 0..M-1$, M stands for the number of mutually exclusive sets of n elements that can be formed in the output of the network, and n determines the number of principal components to be extracted. In this way, each output set represents the n principal components of the FHR signal but at different resolutions.

Thus, these components will provide, at the same time, different views of the same signal to the detection stage. The detection task will be performed using an algorithmic approach, rather than the MLP used in the PCA approach, by combining some of the components previously extracted, and thus avoiding the problem of finding an ideal size for the detection window adjustable to every kind of pattern.

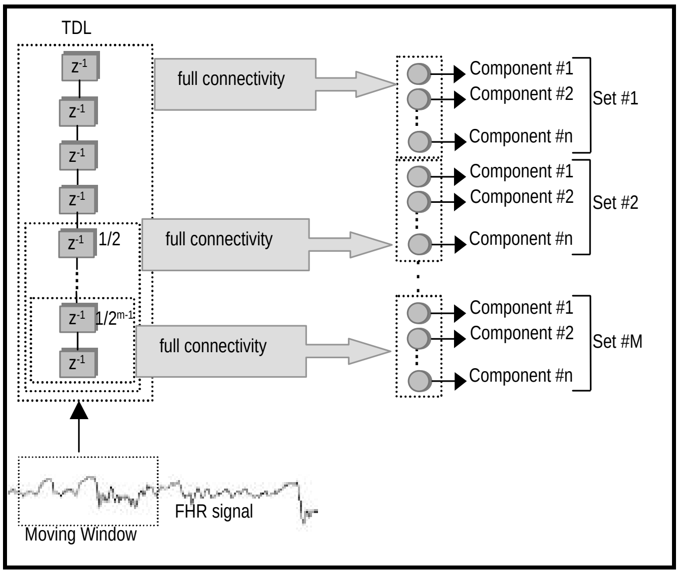

Figure 2: Architecture of a Multi-Resolution Principal Component Analysis Network.

In order to train the neural MR-PCA network a training set was constructed with 124 minutes of FHR signal at a sample rate of 1Hz, containing 76 accelerations and decelerations (equally represented) and selected from 3,450 minutes of records corresponding to 53 different patients. Before being fed to the network, a three-step pre-processing was applied to the training signal:

1) Artefacts were removed,
2) Several baselines were introduced, and
3) The signal was normalised to have zero mean and unity variance.

THE OVERALL PATTERN RECOGNITION MODULE

After several simulations, a TDL of 120 delay units in the input to the MR-PCA network was determined as optimal for our pattern detection purposes. The output layer of the MR-PCA network was constructed so as to obtain the first three principal components of the signal at four different resolutions; it was thus, made up of 12 elements. These four different resolutions were obtained by providing 120, 60, 30 and 15 samples respectively from the input TDL to each set at the output of the network. Figure 3 shows the four versions obtained for the first component.

Let $c_{n,r}$ be the n component taken at resolution r. As can be observed in Figure 3, the first component at the minimum resolution, $c_{1,15}$, represents a smoothed version of the original signal in which accelerations and decelerations are more easily detected. As the resolution is enhanced, this first component is increasingly smoothed until eventually, at maximum resolution $c_{1,120}$ it approximates the baseline of the FHR signal, eliminating fluctuations due to both variability and the patterns of the signal. Therefore, as the component $c_{1,15}$ still contains information about the baseline, a simple subtraction between $c_{1,15}$ and $c_{1,120}$ will provide a very good basis for the detection of FHR accelerations and decelerations. In order to facilitate this detection, the optimal situation will be that in which the observed characteristics in both components, $c_{1,15}$ and $c_{1,120}$, are maximised. A lower number of elements in the input TDL will defy the principle, and a higher number of elements do not show any significant improvement in the characteristics required for the components.

Finally, an algorithmic module performs pattern detection, processing these two components as they are being obtained. First, a softening filter, defined as:

$$f_{1,120}(n)=\frac{1}{2\cdot\Delta+1}\sum_{i=n-\Delta}^{n+\Delta}c_{1,120}(i)$$

is applied to the component $c_{1,120}$ to better approximate the baseline of the FHR, where Δ is equal to 120.

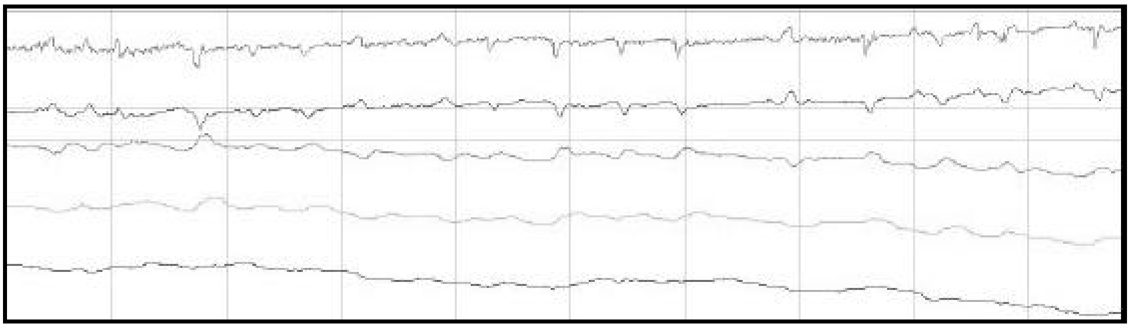

Figure 3: A) Original FHR signal. B, C, D, E) The first principal component of the FHR signal obtained respectively, at sample sizes of 15, 30, 60 and 120 in the input to the MR-PCA network.

Subsequently, a threshold function will determine the presence or absence of a pattern, this function being defined at each instant n as:

$$\text{detection}(n)=\left\{\begin{array}{lll}1 & if & c_{1,15}(n)-f_{1,120}(n)\geq\gamma_d\\ 0 & if & -\gamma_d>c_{1,15}(n)-f_{1,120}(n)<\gamma_d\\ 1 & if & c_{1,15}(n)-f_{1,120}(n)\leq-\gamma_d\end{array}\right\}$$

where γ_d is the detection threshold.

The neural detection system described above is to be integrated as part of the CAFE project (Alonso-Betanzos (1998), Guijarro-Berdiñas (1998A), Guijarro-Berdiñas (1998B)). CAFE is a tightly-coupled hybrid system (combining algorithms with knowledge-based systems and neural networks) developed for fetal monitoring using the non-stress test (Parer (1997)). Specifically, the results obtained by this neural network, in addition to other information, will be used as inputs to the CAFE´s actual diagnostic module, the expert system NST-EXPERT (Alonso-Betanzos (1995), Alonso-Betanzos (1996)), for the intelligent real time monitoring of fetal status.

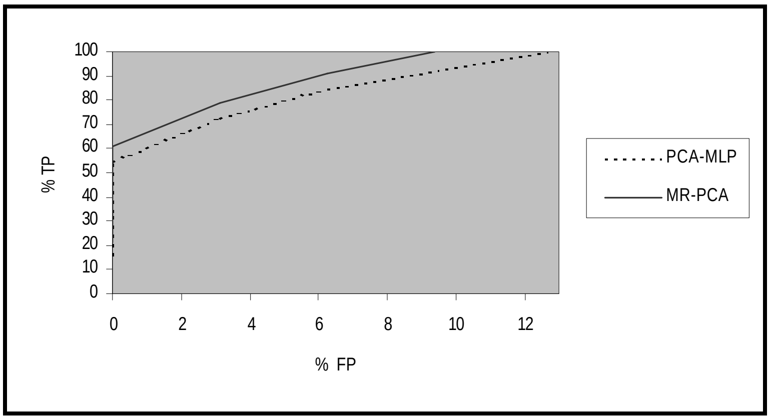

Figure 4: ROC curves comparing the detection levels of the previous PCA-MLP system versus the new MR-PCA system at different detection thresholds.

EXPERIMENTAL RESULTS AND CONCLUSIONS

In order to verify the performance of the MR-PCA system a test set of 33 fetal patterns in a 137 minutes FHR signal was employed. Figure 4 shows the ROC (Receiver Operating Characteristics) curves corresponding to the proposed system versus the standard PCA system, obtained from the test set. These curves display the level of false positives obtained for a given percentage of true positives, whilst varying the detection threshold of the system.

A retrospective validation was also carried out by comparing the performance of the MR-PCA system with the performance of three expert clinicians working at the Maternal-Fetal Section of the Juan Canalejo Hospital in A Coruña, Spain. For this comparison, a validation set of more than 3,000 minutes of recorded FHR signal, corresponding to 46 different patients, was employed. These recordings were separately analysed by the experts, the algorithmic module of the CAFE system, the neural system composed of the PCA and the MLP networks, and also the proposed system. Eventually, 985 accelerations and 588 decelerations were detected in the validation set by either the clinicians or the automatic systems. However, this is a critical domain in which there is no gold standard for a comparison of the results obtained in a FHR signal analysis, and in such cases, methods based on the comparison of results supplied by a system with those supplied by a group of experts, when each is independently faced with the same set of problem data, are employed to facilitate the validation process (Moret-Bonillo (1997)). In this case, percentage agreement and Kappa measurements (Moret-Bonillo (1997)) were used to identify the level of agreement existing between the experts and the developed systems.

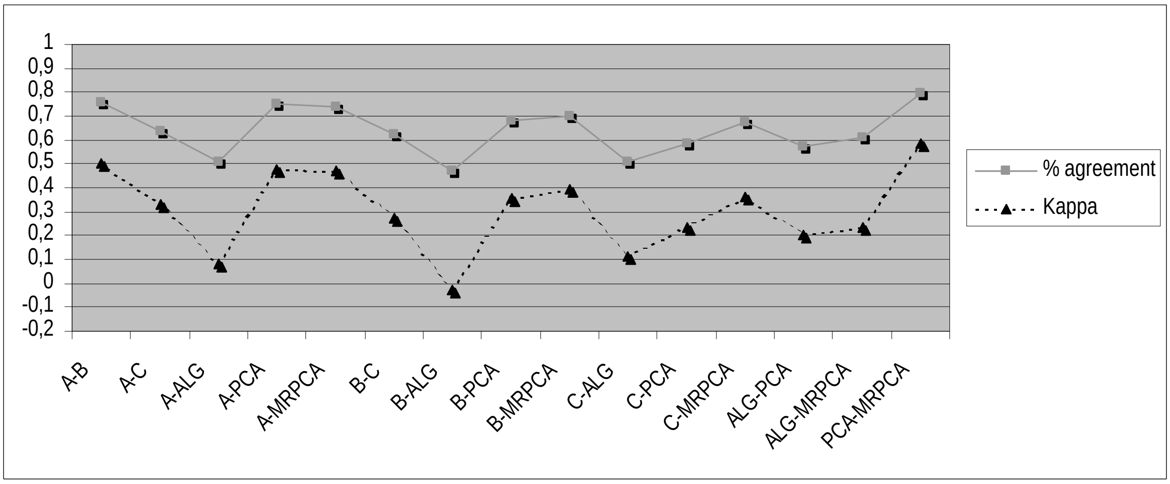

Figure 5: Percentage agreement and Kappa measurements obtained for accelerative patterns.

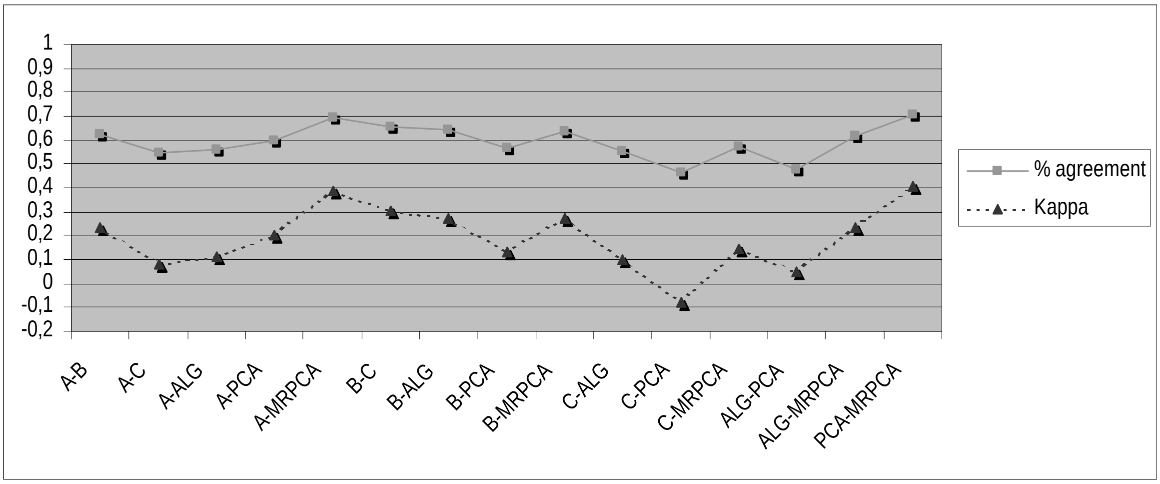

Figure 6: Percentage of agreement and Kappa measure obtained for decelerative patterns.

Figures 5 and 6 show the values obtained by these measurements for accelerative and decelerative pattern detection, respectively. It can be observed that, in the first case (accelerative patterns), the new MR-PCA network produces a similar level of agreement to that of the clinicians and also the PCA-MLP system, even improving the level of agreement with respect to Clinician C. In the case of decelerative pattern detection, the new system produces a higher level of agreement than the PCA-MLP system and again analogous to that obtained among the experts.

It was also verified that, as was expected, the problem of the detection of false positives - due to the presence of patterns of long duration - disappears in the new system, and a total of 89.47 % patterns incorrectly classified by the previous PCA-MLP system have now been correctly detected.

An additional advantage of the proposed system is in the use of the first principal component in the detection task. This component was eliminated in the PCA-MLP system because it mostly contained information about the baseline and if included, the outcome of the system would have been excessively baseline-dependent. Nevertheless, this component also contains information about patterns that is relevant to the detection task. The proposed approach makes use of this component at different resolutions, allowing the removal of baseline influence in pattern detection without eliminating information about the patterns, thus making optimising the procedure.

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