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Cross Signal Identification for PSG Applications

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***Abstract*—**The standard investigational method for obstructive sleep apnea syndrome (OSAS) diagnosis is polysomnography (PSG), which consists of a simultaneous, usually overnight recording of multiple electro-physiological signals related to sleep and wakefulness. This is an expensive, encumbering and not a readily repeated protocol, and therefore there is need for simpler and easily implemented screening and detection techniques. Identification of apnea/hypopnea events in the screening recordings is the key factor for the diagnosis of OSAS. The analysis of a solely single-lead electrocardiographic (ECG) signal for OSAS diagnosis, which may be done with portable devices, at patient's home, is the challenge of the last years. A novel artificial neural network (ANN) based approach for feature extraction and automatic identification of respiratory events in ECG signals is presented in this paper. A nonlinear principal component analysis (NLPCA) method was considered for feature extraction and support vector machine for classification/recognition. An alternative representation of the respiratory events by means of Kohonen type neural network is discussed. Our prospective study was based on OSAS patients of the Clinical Hospital of Pneumology from Iaşi, Romania, males and females, as well as on non-OSAS investigated human subjects. Our computed analysis includes a learning phase based on cross signal PSG annotation.

***Keywords*—**Artificial neural networks, feature extraction, obstructive sleep apnea syndrome, pattern recognition, signal processing.

I. Introduction

THE obstructive sleep apnea syndrome (OSAS) is one of the most common respiratory disorders of sleep. It affects more than 4% of the adult population and is characterized by episodes of upper airway obstruction during 10 or more seconds while sleeping. The disease is caused by the relaxation of the muscles at the base of the throat, leading to airflow obstruction in the upper respiratory tract, manifesting through partial pharynx collapse and reduction of pulmonary effort (hypopnea) or complete suppress of the air flux (apnea),. This recurrent breathing difficulty is associated with increased respiratory efforts which prevent the brain from entering the deep stages of sleep and causes excessive daytime sleepiness. Therefore OSAS reduces the patient`s quality of life and increases the risk of traffic and work accidents. Considerable evidence is available in support of an association between obstructive sleep apnea syndrome and cardiovascular diseases, particularly for systemic arterial hypertension, ischemic heart disease, stroke, heart failure, atrial fibrillation and cardiac sudden death [3].

The pathogenesis of cardiovascular disease in OSAS is not completely understood but likely to be multi-factorial, involving a diverse range of mechanisms including sympathetic nervous system over activity, selective activation of inflammatory molecular pathways, endothelial dysfunction, abnormal coagulation and metabolic deregulation, the latter particularly involving insulin resistance and disordered lipid metabolism.

OSAS, the most frequent of the sleep respiratory disorders (SAS), is defined as the intermittent cessation of breathing during sleep for at least 10 sec, accompanied by more than 4% blood oxygen desaturation, with a frequency of over 5 respiratory episodes per hour, apnea eventually alternated with hypopnea episodes [4]. Repeated apneas induce changes into the electrocardiogram (ECG) due to neuroautonomic and mechanical factors, such as cyclic variation in heart rate, or cyclic variations in ECG amplitude or morphology [5]. The sleeping disorders, and especially apneas, are now diagnosed by polysomnography (PSG) examination (considered to be *golden standard* in this case), especially if performed in a specialized sleep laboratory. A variety indexes are used for evaluate or to categorize the severity of OSAS, the most of them being determined by linear statistics, such as cut-off points of apnea-hypopnea index (AHI). Evaluates like AHI > 5, or AHI > 10, or AHI > 15 are arbitrarily used and have undetermined clinical importance.

We propose a novel technique, based on the processing of solely ECG overnight recording, which is a combination of a nonlinear statistical method, nonlinear principal component analysis (NLPCA), to characterize the recordings, justified by the complex nonlinearity of the system to produce the measured physiological signals. Our prospective study included 87 patients, 68 males and 19 females, aged 34 to 75 years, with clinical suspicion of OSAS. Physical examination, Epworth Sleepiness Scale and overnight polysomnography were performed on all of these subjects, at the Sleep Unit of

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the Clinical Hospital of Pneumology from Iaşi. Only 62 of them proved to have OSAS. The ECG recordings from the PSGs were preprocessed in order to be used for the learning phase of the artificial neural network processing, annotated by cross investigation with other PSG recordings, such as chest and abdomen effort, blood oxygen saturation (SpO2), and air flow (oro-nasal) recordings.

The main goal of the study presented in this paper was to perform pattern discovery in ECG during sleep time-series, with respect to the presence or absence of respiratory events, in order to detect them automatically and even diagnose OSAS. We have used artificial neural networks (ANN) to implement nonlinear analysis, namely NLPCA of ECG signal segments, to characterize obstructive sleep apnea in adult human subjects. Another approach consisted in representing respiratory events in ECG recordings by means of Kohonen type neural networks. The next signal processing step consisted in a support vector machine (SVM) based classification, selecting feature vectors from the previously determined patterns. The following chapters describe the data selection process and these methods.

Another chapter summarizes the simulation results. Computer simulations were performed on one lead ECG recordings from sets of learning and test subjects. Matlab and Simulink were used to implement the analysis framework program designed to classify electrical cardilogical signal patterns. Conclusions resume the results obtained till now with this research method.

II. Methods

A. Nonlinear Principal Component Analysis (NLPCA) Based Feature Extraction from ECG

Nonlinear principal component analysis (NLPCA) is a special case of principal component analysis (PCA), also known as *kernel PCA*, designed to find the eigen feature vectors of the input signal space, that best account for the distribution of specific signals points within it**,** in terms of a best coordinate system. This method provides representations as eigenfunctions of the averaged covariance of the ensemble of the signals processed in the learning phase, in our case the ECG recordings, which will emphasize some significant local and global features they share. Selecting relevant segments of the overnight long term ECG recordings, and adequately pre-processing them, help us characterise respiratory sleep events, eventually correlated with other pathologies.

The NLPCA methods, first introduced by Kramer in 1991 [11], project input data on a nonlinear eigenvectors coordinate system, which ensures the maximization of the variances of the original data, making the discrimination task more feasible. The usual approaches in NLPCA implementation are the artificial neural networks (ANN). We choose the Sanger type unsupervised ANN architecture, with lateral inhibitory connections for the representation layer, to obtain simultaneously convergence to the ordered nonlinear principal components, easier than other NLPCA reported approaches, and very economically implemented in the Matlab Simulink environment. We used previously this approach for EEG signals processing [9]-[10]. The system output and its parameters evolution are described by equations (1), and respectively (1'). Relations (2)-(5) are linked to the nonlinear Sanger learning rule for the **w**(t) parameters tuning.

We obtained convergence of the generalized Sanger's type learning algorithm (1') to ordered eigenvectors of the input space, and for the outputs of the NLPCA layer (2), which are projections of the inputs on this rotated axes of coordinates, for very small learning parameters, corresponding to large time constants learning. The choice of the nonlinearity of the PEs becomes important to the convergence and to the signal representation properties, which may influence, in turn, the further processing performance. We tried sigmoid type nonlinearities for the representation of ECG with NLPCA in a previous work [2], and also hysteresis type nonlinearity, which showed poor convergence to the eigen coordinate vectors in the parameter space. For this research we choose Gaussian type nonlinearity, **f**, with very good convergence properties for the Sanger learning rule.

$$\mathbf{y}(t) = \mathbf{f}\left(\mathbf{w}^T(t)\mathbf{x}(t) + \boldsymbol{\theta}(t)\right) \tag{1}$$

$$\Delta \mathbf{w}_j(t) = \eta(t)\mathbf{y}_j(t)[\mathbf{x}(t) - \mathbf{w}^t_j(t)\mathbf{y}^t_j(t)] \tag{1'}$$

$$\mathbf{w}_j(t) = \left[w_{j1}(t) \quad \cdots \quad w_{jn}(t) \quad \theta_j(t)\right]^T, j = 1,\ldots,m \tag{2}$$

$$\mathbf{w}^t_j(t) = \left[w_1(t) \quad \cdots \quad w_j(t)\right] \tag{3}$$

$$\mathbf{y}^t_j(t) = \left[y_1(t) \quad \cdots \quad y_j(t)\right]^T \tag{4}$$

$$\mathbf{x}(t) = \left[x_1(t) \quad \cdots \quad x_n(t) \quad 1\right]^T \tag{5}$$

JuhaKarhunen si Jyrki Joutsensalo showed in 1995 that equation (1') approximates the solution of the minimization problem:

$$J(w) = E\{\|x - wy\|^2\} \tag{6}$$

A discrimination function was considered afterwards, based on the projections on the eigen axes. Class prototypes are found by nonlinear regression to the input data, with a two layer feedforward network, with the parameters adapted by minimizing the MSE error:

$$E = \frac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m}\left(x^i_j - \hat{x}^i_j\right)^2 \tag{7}$$

where x^i_j and $\hat{x}^i_j$ are, respectively, the input vector and the reconstructed one.

B. Kohonen Feature Map Representations

Kohonen self organizing feature maps (SOM) are unsupervised ANN that may be used to represent multi-dimensional data in a space with reduced dimensionality compared with the original one, as an alternative to the NLPCA resulted representation. Topological relations of the learning data set are conserved. The processing elements (PE) positions map these relations. A K-means type algorithm

adapts the PE neighborhood. The k[th] PE, the closest to the input vector $\boldsymbol{\xi}$, is adapted and his K-distant neighbors together with it:

$$\|\mathbf{W}_k - \boldsymbol{\xi}\| \le \|\mathbf{W}_i - \boldsymbol{\xi}\|,\ i = 1,...,m.$$

$$\mathbf{W}_i = \mathbf{W}_i + \eta\boldsymbol{\phi}(i, k)\,(\boldsymbol{\xi} - \mathbf{W}_i) \tag{8}$$

where the i^{th} PE belongs to the specified neighborhood the k^{th} PE, and $\boldsymbol{\phi}(i, k)$ is the neighborhood function of neuron k.

The neighboring topologically interconnected PE in the Kohonen structure have a synergic activity, rendering the final converged representation for certain initial conditions.
Varying the learning parameter from 0.85 to 0.1 as well as the neighborhood dimension from 15 to 1, and using 500 samples/epoch we obtained convergence after about 3500 epochs.

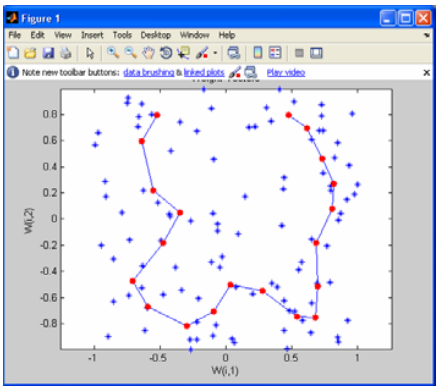

Fig. 1 Apnea SOM representation

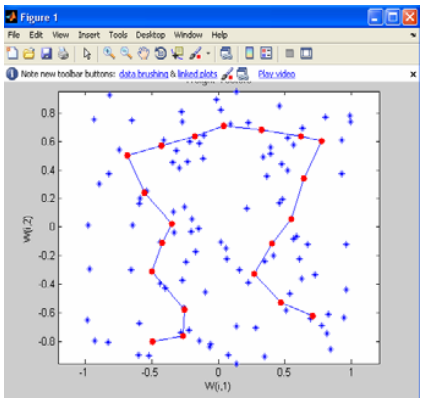

Fig. 2 Hypopnea SOM representation

C. Support Vector Machine (SVM) Classification

SVM was used for the classification and respectively recognition of the ECG signal elements in classes denoting the belonging to a respiration event, apnea or hypopnea, or being outside such an event. We are searching for a better automatic annotation method of respiration events in order to diagnose or characterize SDR diseases, especially OSAS, solely by means of one lead ECG signal processing. In our earlier work we tried classification with a multilayer perceptron structure (MLP) [2]. Other researchers also considered SVM for the monitorization of OSAS suspected patients and correctly diagnose the disease, performing time-frequency signal preprocessing [8], or feature extraction by morphological analysis of the ECG signal [7], in advance. We consider that the best results were reported in [6], where features vectors were extracted from the respiration derived signal (SDR) and heart rate (HR) recordings.

We used SVM in combination with NLPCA. The simulation results are encouraging, and we consider our approach to be simpler and more general, as soon as the system, provided with appropriate signal samples, learned the feature vectors.

SVM are a set of supervised learning methods used for classification and regression, which may be considered as a special case of Tikhonov regularization. Also known as maximum margin classifiers, they solve a min-max constrained optimization problem on the feature vectors space in order to determine the optimal separation hyperplane between classes, namely minimizing the risk of misclassification while maximizing the interclass margin. Nonlinear classifiers with SVM, as our classifier is, proposed for the first time by Bosel, Guyon and Vapnik in [1], replace the inner product function of the linear classifier with a more general kernel function:

$$\min_{f\in\mathcal{H}}\left(\frac{1}{2}\|\Gamma f\|^2 + C\sum_{i\in\aleph}|1 - y_i f(x_i)|_+\right)$$

$$\max_{\alpha}\left(\sum_i \alpha_i{}^2 - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j k(x_i, x_j)\right) \tag{9}$$

$$\text{subject to}: \alpha i \ge 0, \sum_i \alpha_i y_i = 0, i = 1,..,m$$

$$\alpha = (\alpha_1,...,\alpha_m)^T$$

where $x_i \in X \subseteq \Re^m$, $y_i \in \{-1,1\}$, symbolizing the class C_k belonging of sample x_i, for a finite number, K, of known classes, $i \in \aleph$ being the index of the feature sample. Function f is the discriminator function to be determined in some feature Hilbert space, $\mathcal{H}$, and Γ is the regularization operator, for the ill-posed problem. In our approach it is approximated with an artificial neural network structure. Notation $k(.,.)$ in (9) refer to a positive definite kernel function, a Mercer kernel. A very convenient choice is the Gaussian kernel, considered to be a similarity measure:

$$k(x, x') = \exp\left(-\|x - x'\|^2 / 2\sigma^2\right) \tag{10}$$

The NLPCA preprocessing is necessary for the dimensionality extension of data, selection of features conserving the maximum variances, and classes' prototypes estimation, used by the SVM. The maximum margin concept implementation

of the SVM decouples the capacity of the classifier from the input space and at the same time provides good generalization.

III. Simulation Results

The one-lead ECG recordings were obtained from 87 human subjects with clinical suspicion of OSA, PSG investigated at the Sleep Unit from the Clinical Hospital of Pneumology from Iasi, Romania, their PSG recordings being stored in a database in a previous research stage [2]. The overnight recordings of single continuous ECG signals were of approximately 8 hours duration, sampled at 200Hz, with 16 bit resolution, one sample bit representing 5μV. The standard sleep laboratory electrode positions were used (modified V2 lead). We used Somnologica software to label the respiratory events, apnea and hypopnea. Using this information we separated segments of ECG signal corresponding to apnea events, hypopnea events, and normal respiration periods, and concatenate them to form a hybrid signal file, with random mixed segments. Each segment had a corresponding class label. We converted the one dimensional data vector into a 8-dimensional and 23-dimensional data vectors used as inputs to the NLPCA unit. A target file with classes' labels for each record element was also considered. From these files, 20% of the records were used for cross validation, providing prevention from over-fitting or under-fitting by optimal cessation of the learning process, and 20% of the records were used for testing, providing generalization performance. Figs. 3-4 show 8 channels decomposition of some significant ECG segments, accounting for two classes: apnea type respiration events, and hypopnea type respiration events.

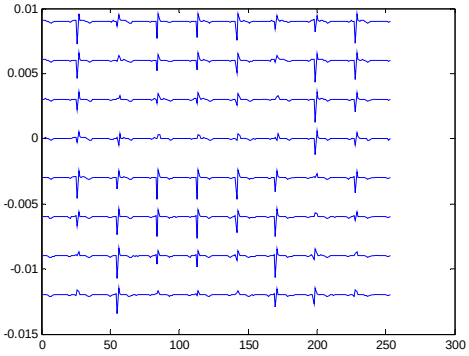

Fig. 3 8-channels decomposition of single-lead ECG signal segment during an apnea type respiration event

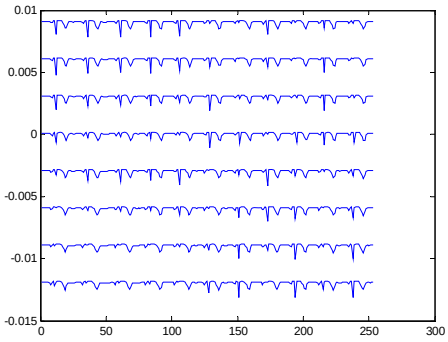

Fig. 4 8-channels decomposition of single-lead ECG signal segment during an hypopnea type respiration event

Fig. 5 shows some of those patterns distribution. We can see now a categorical linear discrimination between classes. Fig. 6 depicts the weights' adaptation for Gaussian type nonlinearity of Sanger layer, in the NLPCA preprocessor, which proved to be the best choice from the convergence point of view. We have also tried the hyperbolic tangent and hysteresis nonlinearities, which shove poor convergence for this type of input data presentation. In Figs. 7 and 8 there are presented 2 classification performances of the same input patterns to the classifier: one for multilayer perceptron type, and the other Gaussian.

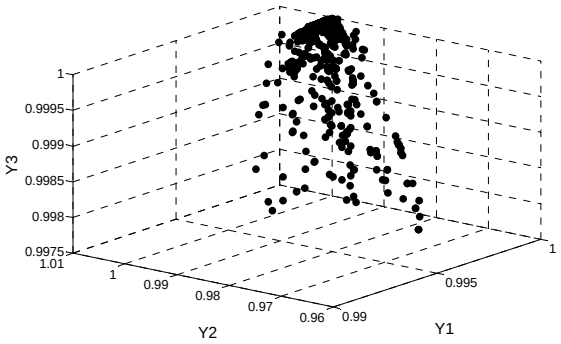

Fig. 5 The most significant 3 of the NLPCA outputs, from the point of view of input data variance maximization

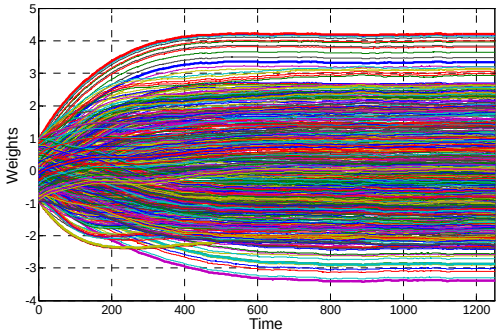

Fig. 6 NLPCA parameter adaptation

Fig. 7 Multi layer perceptron (MLP) classification of NLPCA preprocessed single lead ECG: 3 layer MLP (50-10-1 processing elements (PE)/layer), after 7000 training epochs, MSE≅0.008)

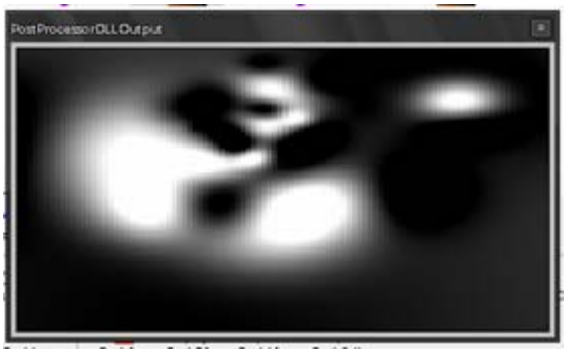

Fig. 8 SVM classification of NLPCA preprocessed single lead ECG, after 150 epochs, 40 PE in the representation layer, MSE≅0.02

IV. Conclusion

This paper presented a method for screening single-lead ECG recordings for automatic annotation of the respiratory events, like apnea and hypopnea. Classifiers based on multilayer perceptron and SVM were used. The 1-D ECG signal was mapped into a higher dimensional space and projected on a rotated, nonlinear, coordinate axes system, providing the means for linear discrimination between classes. NLPCA trained with generalized Sanger algorithm was used for ECG signal preprocessing. There were conservatively retained those principal components which account for 99.9% of the variation in the data set. There seemed to be a significant redundancy in the data set since the NLPCA has reduced the size of the input vectors from 8 and 23 to 3.

Experiments with ECG data show that the neurons in NLPCA become sensitive to different signal patterns. Standard linear PCA algorithms don't have such a separation property.

SVM together with NLPCA input ECG single lead recorded data provided a better classification compared with MLP classification of the same input data preprocessing, from the architectural and consequently computational cost point of view, and also from the classification performance point of view. We intend to extend our research to discriminate between certain pathologies associated with OSAS, and also to use Kohonen representation for multi-class discrimination.

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