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On-line Learning Algorithms for extracting respiratory activity from Single Lead ECGs based on Principal Component Analysis

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Abstract

In this paper we present several statistic gradient algorithms from literature to solve the Principal Component Analysis (PCA) problem. We used a linear artificial neural network forming the basis of the implemented algorithms which is a neat way for on-line computation of the PCA expansion. As convergence is a key-aspect of these algorithms and is crucial for the usefulness in particular applications, we compared the different learning rules with respect to their suitability in ECG signal processing. Recent studies have shown, that a surrogate respiratory signal can be derived from single-lead ECGs by applying PCA. Since the traditionally applied closed-form computations of PCA are numerically demanding, it seems promising to resort to an adaptive approach when dealing with changing environments like the ECG.

1 Introduction

Principal Component Analysis has become an important technique in statistical data analysis with respect to dimension reduction, feature extraction, data-decorrelation and whitening [1]. It was also shown, that even from a single lead ECG, valuable information like morphologic variability, ventricular repolarization, atrial fibrillation or myocardial ischemia can be extracted by PCA [2]. Langley *et al.* have successfully used PCA by eigenvalue and eigenvector decomposition to extract an ECG-Derived Respiration feature from a single lead ECG [3]. The PCA Problem can be stated as follows: Find an orthogonal transformation matrix **A** such that the elements of a centered measurement vector **x** become uncorrelated:

$$\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x} \qquad (1)$$

Thus, the covariance matrix of the transformed dataset **y** is diagonal. It can be shown that PCA is equivalent to variance maximization of the principal components (PC), which are represented by the elements of **y** and that the solution of maximizing the variance is given by the unit-length Eigenvectors of the covariance matrix $\boldsymbol{C_x}$ of **x** [1]. Following this approach it would be necessary to re-estimate $\boldsymbol{C_x}$ and re-calculate the eigenvectors periodically, which can be critical when high speed processing of on-line arriving data samples is needed. This makes adaptive, computationally efficient on-line learning algorithms very attractive. Gradient algorithms based on neural networks learning rules allow the estimation of eigenvectors without using second-order-statistics (SOS) at all [4].

In the first part of Section 2 we depict the underlying PCA layer. In the second part we give a brief overview of the different gradient ascent algorithms and their learning rules whereas in the third part we introduce the datasets and how they are applied to them. Section 3 presents the obtained results and Section 4 finishes with a short discussion and summarized conclusions.

2 Methods

2.1 PCA Neural Network

A neural network has been proposed as an adaptive system that receives streaming-data and estimates the principal components by Oja [5]. This idea has led us to implement a linear PCA layer as shown in figure 1 which is used by the learning algorithms described in the next subsection.

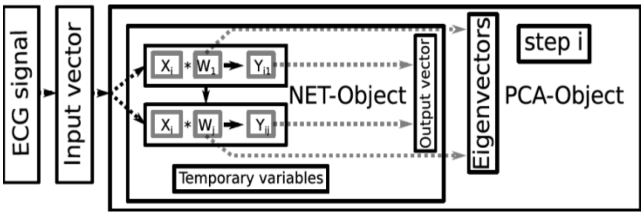

Fig 1 PCA NN Layer used by learning algorithms

2.2 Learning Algorithms

The learning algorithms work as an iteration process on the dataset where the weight-vectors $\boldsymbol{w_i}$ are adjusted in each step and finally converge to the corresponding eigenvectors. The gradient algorithm finds the local minima in a multidimensional contrast function $\Psi(\boldsymbol{w})$ with the help of an update rule (Eq. 2). The value of the function alpha specifies the learning rate.

$$\boldsymbol{w}(t) = \boldsymbol{w}(t-1) - \alpha(t)\frac{\partial\Psi(\boldsymbol{w})}{\partial\boldsymbol{w}} \qquad (2)$$

In the scope of this study we have implemented Oja's Rule and Stochastic Gradient Ascent (SGA) [5], a modification of the generalized Hebbian algorithm (GHA) [6], Adaptive Principal Component Extraction (APEX) [7], the Projection Approximation Subspace Tracking (PASTd) [8] and a fast online algorithm for PCA (RTpca) proposed by [9]. All considered algorithms have linear complexity. The point of interest then focuses on the estimated eigenvectors which are compared against those, gained by classical closed-form computation of the covariance matrix $\boldsymbol{C_x}$.

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At this stage all algorithms have been implemented in MATLAB although no sophisticated functions have been used so that porting them to C should be an easy task.

2.3 Dataset

The single lead channels used in the datasets were obtained from Fantasia Database of Physiobank ATM which contains a single channel ECG and a respiratory signal sampled with *250* Hz [10]. With the help of the supplied database-ECG-annotations *161* samples including P-wave, QRS-complex and T-Wave have been extracted, thus obtaining N beats of N consecutively following QRS complexes of one specific dataset. A $161xN$ input matrix $\mathbf{X}$ is then built by these N beats according to [3]. Finally the algorithms are consecutively supplied with vector-samples $\mathbf{x(i)}$ from $\mathbf{X}$.

3 Results

To evaluate the performance of the stated algorithms the main criterion has been the convergence of the estimated eigenvectors with respect to their length and angle as they become orthonormal and tend to the theoretically correct eigenvectors [4]. These vectors are compared to those computed by eigenvector decomposition of the covariance matrix $\boldsymbol{C_x}$.

Figure 2 a) shows the process of convergence of the absolute value of the first four weight-vectors computed by the RTpca algorithm. Similar results are obtained for the first two eigenvectors by the other algorithms. However, not all algorithms estimated the minor components accurately as can be seen in figure 2 b). This could be improved by more sophisticated learning rate adjustments [4]. First experiments showed that at least *100* QRS complexes which is still less than two minutes should be taken into account to achieve a reasonable foundation for stable convergence.

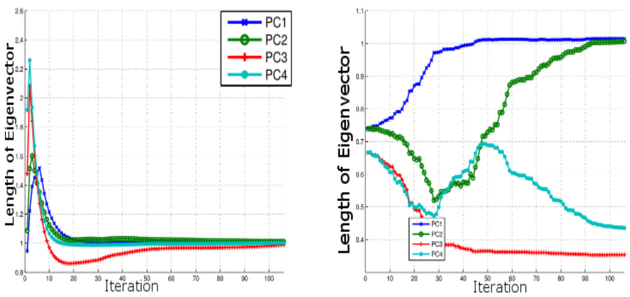

Fig 2 Convergence of the first PCs for a) RTpca- and b) the SGA-algorithm

According to [3] respiration can be found in the third or fourth component of the ECG. This could be confirmed by the results of our implementations. Figure 3 shows the estimated fourth principal component, the recorded respiratory signal and their cross-correlation (bottom).

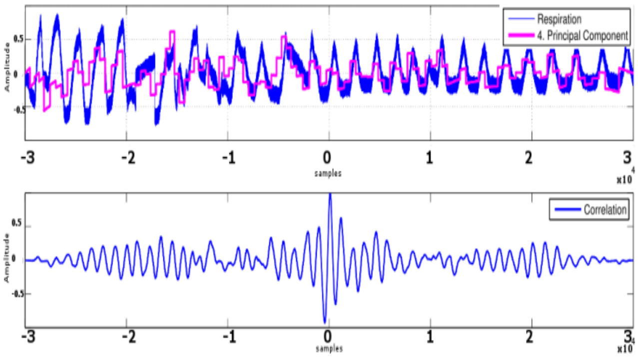

Fig 3 Recorded respiratory signal and fourth PC (top), Correlation (bottom) of the offset corrected signals

The main peak in the cross-correlation at zero shows the strong correlation between the estimated fourth component and respiratory activity.

4 Conclusion

Using several NN based adaptive algorithms we were able to successfully estimate principal components from the ECG. While all algorithms were able to estimate the first and second PCs, some algorithms failed in estimating the minor PCs. It should be remarked, that most successful estimations of the third and fourth eigenvectors were achieved by the RTpca algorithm for the ECG data sets. However, optimizing the learning rate, a crucial and also delicate factor in all online learning algorithms, seems promising to improve the results for the less successful ones. We were also able to show a distinct correlation in one of the minor components with respiratory activity, thus confirming the results from [3] with our approaches. An automatic and robust classification of the corresponding principal component containing respiratory activity has to be implemented in future work.

As there are no annotations with on-line obtained data, it should be mentioned, that this approach will always depend on the quality of the preceding QRS-complex detection algorithm. This could become a difficult task when artifact contaminated signals are processed and only limited processing power is available. Especially signals like the ECG, acquired in ambulatory situations are very liable towards artifact components arising from environmental and experimental factors [11].

The on-line algorithms themselves are quite efficient and not very resource demanding, making them attractive for implementations on low performance systems like mobile sensor-nodes. A more sophisticated study is planned on data acquired by a wireless Body-Sensor-Network developed at our department, where a respiratory signal and ECG can be simultaneously recorded in home-monitoring [12].

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5 Literature

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