Detection of the EEG Artifacts by the Means of the (Extended) Kalman Filter

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Abstract

This paper presents a new approach for detection of artifacts in sleep electroencephalogram (EEG) recordings. The proposed approach is based on Kalman filter. The idea of this approach consist in embedding the AR model into the Kalman Filter which makes possible to use such KF AR (Kalman Filter AR) models for linear prediction of non-stationary signals. Such model can be set up to detect and follow discrete dynamic changes of the signal. For detection of the EEG artifacts we have exploited the evolution of the state noise - increase in state noise indicate the dynamic change of the signal. The evaluation of the results was done by the Receiver-Operator Characteristics (ROC) curves - in terms of the specificity and the sensitivity. For 90% of the specificity the best achieved value of the sensitivity using KF AR model was 33%. In order to achieve better results we have tried the following modification: instead of the Kalman Filter we have used extended Kalman Filter and instead of the AR model a neural network. The preliminary results look promissing: for 90% of the specificity we have achieved 65% of the sensitivity.

Keywords: Kalman Filter, AR model, Extended Kalman Filter, RBF Neural Networks, EEG artifacts

1. Introduction

Electroencephalography (EEG) is a medical technique that measures brain function by analysing the scalp electrical activity generated by the brain structure. Analysis of the EEG recordings is usually done by EEG experts, which must carefully inspect these recordings. However this process is generally very time-consuming, because of the vast amount of the data. For this reason many different automated methods have been proposed to reduce the time needed for visual inspection.

One of the main problems in the automated EEG analysis is the detection of the different kinds of interference waveforms (artifacts) added to the EEG signal during the recording sessions [1]
We can look at artifacts, as they are waves or group of waves that are produced by technical or other disturbances, which are not due to brain activity. The most important reasons for occurrence of the artifacts are the movements of the patient during recording session and the normal electrical activity of the heart, muscles and eyes [1]. Recognition and elimination of the artifacts in EEG recordings is complicated task, but essential to the development of practical systems [2]. A valid artifacts processing strategy should on the one hand minimise the amount of data that have to be eliminated and on the other ensure that the obtained results are not influenced by undetected artifacts [3]. In case of visual inspections the artifacts can be relatively easy detected by the EEG experts. However, during the automated analysis these signal patterns often cause serious misclassifications thus reducing the clinical usability of the automated analysing systems [1].The aim of this work is to detect such artifacts in sleep EEG recordings.

The paper is organized as follows. In Section 2 the method for detection of sleep EEG artifacts is described. Section 3 describes the achieved results in terms of the specificity and the sensitivity and Section 4 contains the comparison of these results and the results reported in [8]. Section 5 is devoted to conclusions and future work.

2. Methods

This Section describes the approaches that we have used for sleep EEG artifacts detection. The first subsection describes the original approach based on the Kalman Filter autoregressive (KF AR) model as defined in [4], where it is shown how such model can be set up to detect and follow discrete dynamic changes - and this was the main idea, which we have used for the EEG artifacts detection. The second subsection describes the modification of the original approach.

2.1. KF AR model

The AR model is an acronym for the autoregressive model, which is a linear predictor used for modelling stationary time series [4]. The KF AR model is an acronym for the Kalman Filter AR model, which is defined by the following state-space equations according to [4]:

$$\theta_{t+1} = \theta_t + \mathbf{w}_t \qquad \mathbf{w}_t \sim N(0, \mathbf{Q}_t) \tag{1}$$
$$y_t = \mathbf{H}_t \theta_t + v_t \qquad v_t \sim N(0, \sigma_t^2), \tag{2}$$

where t is a time index, θ_t is a state vector of the system at time t - the components are the time-varying AR coefficients. y_t is a measurement at time t, $\boldsymbol{H}_t$ is a measurement matrix, where $\boldsymbol{H}_t = [y_{t-1}, y_{t-2}, \ldots, y_{t-p}]$. $\boldsymbol{w}_t$ is a state noise and v_t is a measurement noise. $\boldsymbol{Q}_t$ is a covariance matrix of $\boldsymbol{w}_t$ and σ_t^2 is a variance of v_t. It is assumed that $\boldsymbol{w}_t$ and v_t are zero mean white noises and are independent of each other.

The aim of the KF is to estimate the state of the system from measurements, which contain random errors (for detailed description of the KF algorithm see [5]). The idea of the KF AR model is that by embedding the AR model into the KF it is possible to use such model for linear prediction of nonstationary signals [4]. The state vector (vector of the AR coefficients) of such KF evolves in time and its evolution makes possible the continuous tracking of a nonstationary signal. In [4] it is shown how can be the KF AR model sets up to detect and follow discrete dynamic changes. This can be achieved by updating the state noise ($\boldsymbol{w}_t$) on-line - increase in the state noise allows the KF to jump to the next dynamic regime. There are several methods for updating the state noise covariance matrix $\boldsymbol{Q}_t$ (and thus the state noise). In our experiments we have used the method, where it is assumed that the state covariance matrix $\boldsymbol{Q}_t = q_t \boldsymbol{I}$. Thus this method is based on updating the variable q_t (for detailed description see [6]).

The evolution of the variable q_t (or the state noise covariance matrix $\boldsymbol{Q}_t$ (and thus the state noise) was used for the detection of the artifacts or in other words for marking the seconds as artifactual or clean - increase in state noise indicate the dynamic change of the signal. This marking was based on the selection of the proper value for the threshold in such a way, that every second containing q_t larger than the threshold was marked as artifactual. Let us remark that the number of q_t involved in one second equals to the number of samples recorded per one second.

Table 1: Comparison of the results achieved with KF AR model, EKF NN model and of the results reported in [8]. sens. is the acronym for the sensitivity.

	KF AR model		EKF NN model		results [8]
	date set A	data set B	data set A[1]	data set A[2]	
specificity	sens. (std)	sens. (std)	sens. (std)	sens. (std)	sens. (std)
90%	33% (9)	24% (11)	65% (7)	32% (13)	21% (-)
95%	27% (8)	18% (7)	55% (8)	22% (11)	26% (-)
99%	17% (7)	9% (3)	33% (12)	11% (7)	33% (17)

2.2. EKF NN model

This subsection briefly describes the modification of the original approach (see 2.1). In this modification we have used extended Kalman Filter (EKF) instead of the Kalman Filter and the RBF NN (radial basis function neural network) instead of the AR model.

The EKF is extended version of the KF algorithm for non-linear systems. The essence of the EKF is simply to apply the KF on each time step to a linearized version of the problem, where each linearization is performed about the most recent state estimate available [6]. For EKF NN model we have used the following state-space equations [6]:

$$\theta_{t+1} = \theta_t + \mathbf{w}_t \qquad \mathbf{w}_t \sim N(0, \mathbf{Q}_t) \tag{3}$$

$$y_t = \mathbf{g}_t(\theta_t) + v_t \qquad v_t \sim N(0, \sigma_t^2), \tag{4}$$

where the state vector θ_t =[centers, bias, weights] and $\mathbf{g}_t(\cdot)$ is a non-linear vector function of the state that is in this model represented by the RBF NN. For the detailed description of the EKF algorithm see [6].

3. Results

This Section describes the results of our approaches for EEG artifacts detection. For these experiments we have used two data sets: A and B, which were selected from different all-night recordings from the database of the project SIESTA [2]. The data set consists of the raw data - six EEG time series (recorded from six electrodes). To each of these data sets we have had also the corresponding marker file, which contains an artifact marking of the EEG recording done by the EEG experts. An example of the EEG signal together with the EOG artifact can be seen in the Figure 1.

The evaluation of the results was done by the Receiver-Operator Characteristics (ROC) curves - in terms of the specificity and the sensitivity (see [7]). Because the correct classification of the EEG is clinically more important than the detection of all possible artifacts, the good result is the one for which the specificity is very near its maximal value (100%) and at the same time for which the sensitivity is the higher the better (maximum = 100%). In this way we can also ensure that the minimal amount of the clean seconds will be lost. Thus we are interested in the specificity from 90% to 100% and for the corresponding values of the sensitivity.

The results of the approach based on KF AR model are summarized in the Table 1, where the values of the sensitivity are the mean values over the electrodes and std is an acronym for standard deviation. The data set A is considered as a training set and data set B as a test set. For the detailed description of these results see [7].

The preliminary results of the approach based on the EKF NN model are also depicted in the Table 1. Here the 1st half of the data set A (A^1) was considered as a training set and the 2nd half (A^2) as a test set. In this model we have used RBF NN with 5 inputs, 10 hidden neurons and 1 output. The centers of the radial basis functions were initialised by the k-means algorithm and the widths were all fixed and set to the mean distance between the centers.

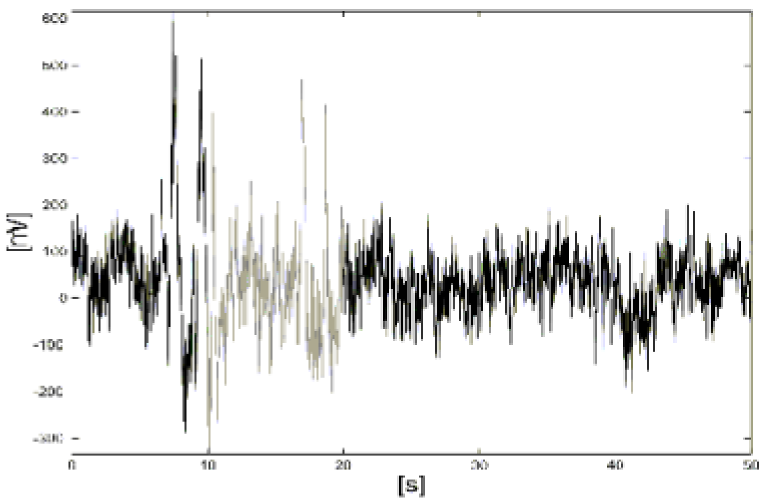

Figure 1: An example of the EEG signal together with the EOG artifact (gray color).

4. Discussion

In this Section we will compare our results with the results reported in [8] (the authors have also used the EEG data sets from the SIESTA database and have evaluated their results with the ROC analysis too.) - see the Table 1. It is easy to see that for both of our approaches the results achieved at the training set (A resp. A^1) are better than the results achieved at the test set (B resp. A^2). We can also notice that on both data sets the results achieved with the EKF NN model are better than the results achieved with the KF AR model. When we compare the results achieved with the KF AR model and the results in [8] we can see that for the specificity of 90% and 95% are the data set A results slightly better while for 99% are worse. Taking the data set B instead of the data set A only the results for specificity of 90% are slightly better, otherwise they are worse. Now we will compare the results of the EKF NN model with the results in [8]. For the specificity of 90% and 95% are the results at the data set A^1 more better than in [8] and for 99% are the same. With the data set A^2 is the situation the same as with the data set B.

5. Conclusions and Future Work

In this paper we have used the two approaches for sleep EEG artifacts detection. The first one is based on the KF AR model. And the second one is the modification of the previous approach, where instead of the AR model the RBF NN was used and instead of the KF the EKF was used. For marking the seconds of the EEG recordings as clean or artifactual we have exploited the evolution of the state noise (variable q_t)- increase in the state noise indicate the dynamic change of the signal. In future we would like to more examine the EKF NN model in order to see if it is possible to obtain better results than the results achieved till now with this model.

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