ARTEFACT DETECTION IN SLEEP EEG BY THE USE OF KALMAN FILTERING

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Abstract: Inverse filtering can be used to identify transient events. Often, artefacts in the EEG are such transient events. Sleep EEG data of 8 eight European sleep labs were scored in 1s-epochs for 9 types of artefacts. The area under the ROC curve (AUC) was 0.857 and 0.898 for muscle and movement artefacts, respectively. Kalman filtering can be used to estimate adaptive autoregressive (AAR) parameters and apply adaptive inverse filtering, simultaneously. The variance of the prediction error can be used as a indicator for muscle and movement artefacts.

Introduction

Inverse filtering can be used for identifying transient phenomena within coloured background noise. The principle of inverse filtering works as following: It is assumed that the EEG signal Y_t is generated by an stationary autoregressive (AR) process

$$Y_t = a_1 Y_{t-1} + a_2 Y_{t-2} + ... + a_p Y_{t-p} + X_t \qquad (1)$$

X_t is the innovation process, assumed to be a zero mean, white noise process $X_t = N(0,\sigma^2_x)$ with variance σ^2_x. Once the AR parameters a_i are identified, the inverse filtered process E_t (2) can be generated.

$$E_t = Y_t - \hat{a}_1 Y_{t-1} - \hat{a}_2 Y_{t-2} - ... - \hat{a}_p Y_{t-p} \qquad (2)$$

As long as the signal is stationary, also E_t is stationary, especially the variance σ^2_E is constant. But in case of a non-stationarity, (the variance of) the prediction error increase.

The principle was used extensively for adaptive segmentation of EEG [1], whereby it was assumed that the AR parameters are constant for same time. Then a transient event occurs, afterwards the AR parameters are constant again. In that case the AR parameters were identified with the Burg or Yule-Walker approach form a short period of time. Next the AR parameters were applied inversely (2) to the signal. The inverse filtered process is then used for identifying transients in the EEG. Statistical tests can be used to detect whether the variance has changed significantly or not.

It is known that the patterns of sleep EEG change with time, but not necessary fast. Therefore, a time-varying AR model for describing the sleep EEG is considered. Unfortunately, the EEG is contaminated by artefacts. Especially muscle artefacts are often such transient events. In this paper it will be investigated how an AAR model [2] can be used for identifying transient events, like artefacts.

Materials and Methods

Experts scored 90 minutes of 15 polysomnographic sleep recordings with 7 EEG channels from 8 European sleep laboratories. Different sampling rates of 100, 200 and 256Hz were used. Nine types of artefacts (EOG, ECG, EMG, movement, failing electrodes, sweat, 50Hz, breathing and pulse) were distinguished and scored on a 1 second resolution (total 563 192 1s-epochs). (Nearly) no pulse and breathing artefacts were identified [2].

The sleep EEG can be modelled by an AAR model, meaning that the parameters in (1) can change with time. It is assumed that the process is nearly stationary, i.e. the parameters change slowly. Kalman filtering was used to calculate AAR parameters [3] as well as the one-step prediction error process.

$$E_t = Y_t - \hat{\mathbf{a}}_{t-1}^T \mathbf{Y}_{t-1} \qquad (3)$$
$$V_t = (1-UC)\, V_{t-1} + UC^* E_t^{\,2} \qquad (4)$$
$$\mathbf{k}_t = A_{t-1} \mathbf{Y}_{t-1} / (\mathbf{Y}_{t-1}^T A_{t-1} \mathbf{Y}_{t-1} + V_t) \qquad (5)$$
$$\hat{\mathbf{a}}_t = \hat{\mathbf{a}}_{t-1} + \mathbf{k}_t E_t \qquad (6)$$
$$\mathbf{A}_t = A_{t-1} - (1+UC)\, \mathbf{k}_t \mathbf{Y}_t^T A_{t-1} + UC^2 {*} \mathbf{I} \qquad (7)$$

Y_t is the recorded EEG signal, E_t the inverse filtered process and p the model order. The difference compared to a stationary AR model is that the parameters $a_{1,t} ... a_{p,t}$ can vary with time. It is assumed that the parameters change only slowly [3]. The vector notation $\hat{\mathbf{a}}_t = [\hat{a}_{1,t} \dots \hat{a}_{p,t}]^T$ and $\mathbf{Y}_t = [Y_t \dots Y_{t-p+1}]^T$ is used. $\mathbf{k}_t$ is the Kalman gain vector and $\mathbf{A}_t$ is the covariance matrix for the estimates of $\mathbf{a}_t$ [3]. The initial values $\mathbf{a}_0$ and $\mathbf{A}_0$ were zero vector and the identity matrix $\mathbf{I}_{pxp}$ respectively, of order p. The update coefficient UC=0.001 and the model order p=10 were chosen.

The Mean Squared Error (MSE) was calculated by squaring and averaging of the prediction error E_t in each 1s-epoch. A threshold applied to MSE can be used for detecting artefacts. Usually sensitivity and specificity describes the quality of the detector for a given threshold. The Receiver-Operator-Characteristics (ROC) display the Sensitivity vs. 100%-Specificity for different detection thresholds. If the ROC curve is diagonal (Sensitivity = 100% - Specificity), the area-under the ROC curve (AUC) is 0.5, no correlation between expert scoring and output can be observed. The ROC curve can be used to identify the optimal threshold for a fixed cost function. In this case the threshold is not known; therefore AUC is used as a measure for the detector quality.

Results

In Fig. 1 the ROC curves for each type of artefact are shown. The area under the ROC curve (AUC) is a measure for the discriminative power of the detector.

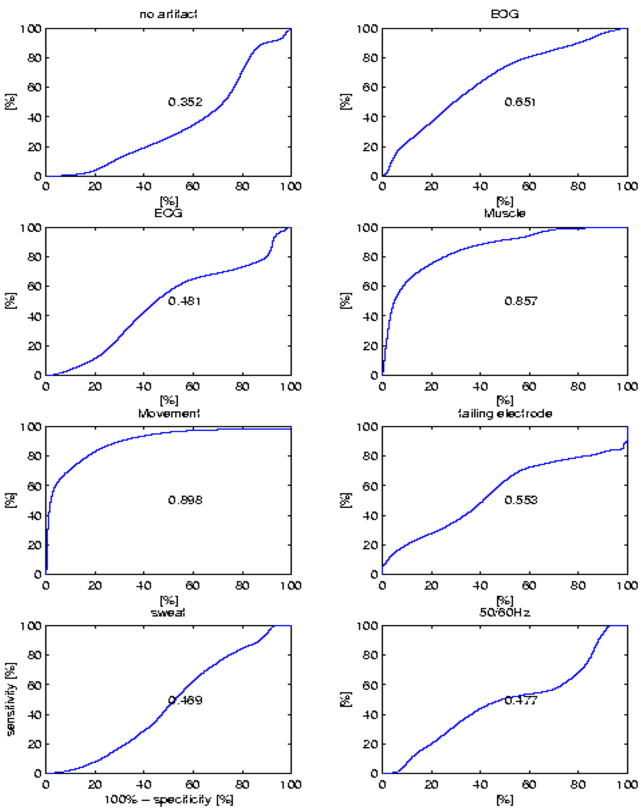

Figure 1: ROC curves of the MSE versus the expert scoring for: 'no artefact' (top left), 'EOG' (t.r.), 'ECG', 'muscle', 'movement', 'failing electrode', 'sweat', '50/60Hz' (b.r.).

The AUC shows how well the MSE parameters indicates a certain artifact. The ROC curve for "no artifact" is below the diagonal SENSITVITY=100%-SPECIFICITY. This means that a larger MSE value indicates an artefact, but not 'no artefact'. The AUC for any artefact is 1 - 0.352 = 0.648.

For muscle and movement artefacts the AUC is 0.857 and 0.898, respectively. In a separate step the muscle and movement artefacts were combined with a logical "OR" operator. The AUC for both artefact types yields a value of 0.870; the AUC for Muscle "AND" Movement artefacts was 0.947.

Discussion

The same model order *p* and update coefficient *UC* were used for recordings with different sampling rates. The model order p and the update coefficient UC were derived from the results in [3]; especially they were not optimised for the various sampling rates.

Two steps were necessary in the traditional approach of inverse filtering based on a stationary AR model. At first the AR parameters (i.e. filter coefficients) had to be identified, in a second step the filter was applied inversely to the signal. But when using an AAR approach, both steps are performed simultaneously. This is an advantage in on-line analysis, when future samples points are not available at estimation time. The limitation to the 1s-time resolution can be overcame by using the adaptive estimated variance V_t (4) instead of 1s-based MSE. One limitation of the method is that after a transient event the AAR estimates do not describe the EEG signal well.

The detection of muscle and movement artefacts shows that adaptive inverse filtering can be used to detect transient phenomena.

Conclusions

The estimation methods for identifying AAR models, describe simultaneously the time-varying behaviour of the sleep EEG with the AAR estimates, as well as transient phenomena like muscle and movement artefacts with the variance of the residual process.

REFERENCES

[1] H.M. Praetorius, G. Bodenstein, and O. Creutzfeld, Adaptive Segmentation of EEG records: A new approach to automatic EEG analysis. *Electroenceph. Clin. Neurophysiol*. 42:84-94, 1977.

[2] A. Schlögl, P. Anderer, M.-J. Barbanoj, G. Klösch, G. Gruber, J.L. Lorenzo, O. Filz, M. Koivuluoma, I. Rezek, S.J. Roberts, A. Värri, P. Rappelsberger, G. Pfurtscheller, G. Dorffner, Artifact processing of the sleep EEG in the SIESTA project. *Proc. EMBEC'99*, Vienna. 1999.

[3] A. Schlögl and G. Pfurtscheller, Estimation of Adaptive Autoregressive Parameters using Kalman filtering. Technical Report, Dept. for Medical Informatics, Univ. of Techn. Graz., 1999.