ADAPTIVE AUTOREGRESSIVE PARAMETERS FOR A BRAIN-COMPUTER-INTERFACE EXPERIMENT

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ABSTRACT:

In an online EEG discrimination task continuous feedback was presented. The EEG was recorded during imagination of left and right hand movement and analyzed with adaptive autoregressive parameters. The parameters discrimination was fed back in form of a rectangular bar on a computer screen over a period of 4 seconds. An online classification result of more than 90% was obtained after a few sessions.

I. INTRODUCTION

Online analysis and classification of EEG data is the main task in an EEG-based Brain Computer Interface (BCI). Such a BCI transforms specific mental activity (thoughts) into signals to set up a new communication system which can be used by subjects with severe motor disabilities [1, 2 3, 4]. An EEG-based BCI often uses the band-power of selected frequencies, which are classified with a linear threshold [5] or an artificial neural-network [6,7].

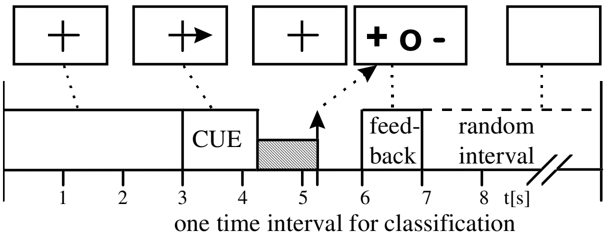

Figure 1: Scheme of BCI4c paradigm that has been used. Above the time axis, the images displayed on the screen are depicted.

A typical example used in the Graz-BCI is decribed in Fig.1. First the the subjects were given a few seconds resting time, then the CUE (arrow to the left or right) was presented. The cue indicated the side of movement (imagination). Then there was one (sometimes two) timepoints for classification, followed by the feedback at a fixed timepoint. At the end of one trial there was a interval of random length with an empty screen.

The online classification was obtained by an artificial neural net based on Learning vector quantization. The power of pre-selected frequency bands was used as input features. The frequency band was determined individually for every subject, by searching for the most reactive frequency band.

The new of idea is:

- to give the feedback immediately without delay.
- to estimate EEG parameters adaptively to obtain a (time-) continuous feedback
- to give not only a qualitative (correct or wrong) but also a (value) continuous feedback

Furthermore the need for real-time evaluation has to be fulfilled.

II. METHOD

To meet the requirements an adaptive autoregressive model was chosen to describe the event-related EEG variation for the following reason:

- A stochastic model describes well the random behavior of the EEG
- an adaptive method provides parameters with a high time resolution
- As side-effect no frequency band has to be selected.

A simple linear combiner was used as classifier. Therewith the weight vector was easily to obtain by linear discriminant analysis (LDA).

An AAR model describes the signal Y_t in the following form:

$$Y_t=a_{1,t}Y_{t-1}+a_{2,t}Y_{t-2}+...+a_{p,t}Y_{t-p}+E_t \qquad (1)$$

Whereby, in the ideal case, E_t is a purely random or white noise process with zero mean and variance σ^2_E. The difference to an AR model is that the parameters $a_{1,t}$ ... $a_{p,t}$

can vary with time. However, it is assumed that the parameters only change very slowly. For a detailed discussion of non-stationary time series see also Priestley [8].

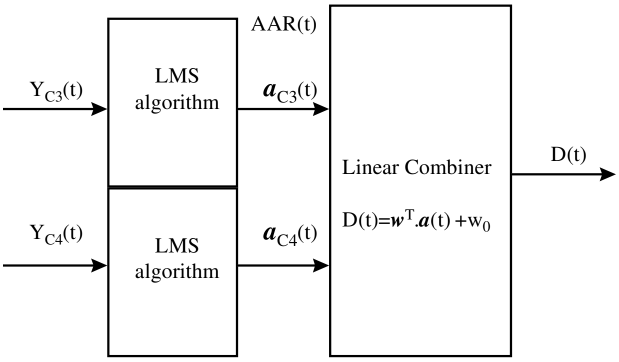

Figure 2: Online processing of EEG data to calculate the feedback D(t). D(t) determines the length of the bar, *w* are the weight factors which are obtained by Linear Discriminant Analysis of previous BCI sessions.

The AAR parameters were estimated with the Least-Mean Square (LMS), characterized by the following update equations [9,10]:

$$E_t = Y_t - a_{1,t-1}Y_{t-1} - \ldots - a_{p,t-1}Y_{t-1} \qquad (2)$$

$$a_{i,t} = a_{i,t-1} + c\, E_t Y_{t-i} \quad i=1 \ldots p \qquad (3)$$

with

$$c = UC / \mathrm{var}\{Y\} \qquad (4)$$

The update coefficient UC=0.004 was chosen as a trade-off between the speed of adaptation and the accuracy of the estimated AAR parameters [11]. The total power of the signal var{Y} and the initial AR parameters $a_{i,0}$ were obtained by previous EEG recordings of the same subject. The model order was chosen with 6. No artifact detection was used.

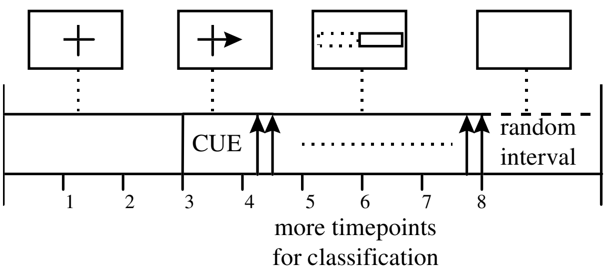

Figure 3: Scheme of the new BCI4e paradigm, the arrows indicate the display of a bar on the computer screen.

The weight vector ***w*** and threshold w_0 were obtained by Linear Discriminant Analysis (LDA) of previous sessions with the same subject. The estimated parameters were smoothened, afterwards the size D of the feedback bar was calculated and displayed every ¼ second. In Fig. 3 the new BCI paradigm is sketched.

III. RESULTS

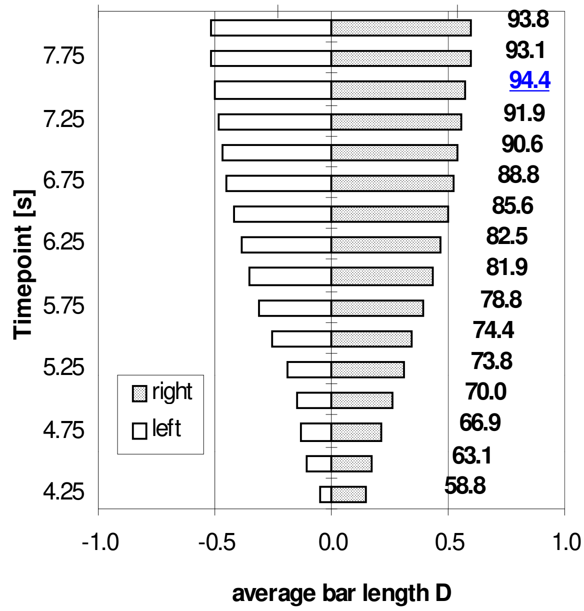

Figure 4: Average distance D(t) for left and right imagined hand movement and percentage of the correctly classified trials across the classification time t

In Fig. 4 the results of one new BCI experiment can be seen. The x-axis denotes the average size of the distance D(t) for imagined left and right hand movement respectively. The y-axis shows the increasing timepoints that were used for classification. Classification was done using D(t). Whenever D(t) > 0 then it was classified as „right“ otherwise it was classified as „left“. The classification accuracy for each timepoint is displayed on the right hand side in bold numbers. Note, that at second 7.5 the highest classification rate occurs with 94,4%; 151 trials out of 160 were as correct classified.

IV. DISCUSSION

The crucial point in this paradigm is the distance D, which depends on the estimates of the EEG parameter and the weight vector $\boldsymbol{w}$. Therefore, it is a prerequisite to very carefully estimate the parameters. An UC to high would give estimates with a high variance, an UC to small would not be able to detect the changes in the EEG. In [11] the optimal UC was found by minimizing the error process. This ensures that a good compromise between the adaptation speed and the erratic changes of the bar length is found.

The weight vector $\boldsymbol{w}$ is the second important factor. It defines the discrimination between the two target patterns and can be easily obtained by LDA; no neural-network based classifier has to be used.

For the estimation of the EEG parameters an adaptive method is chosen. The advantage is that the time-resolution of the computed parameters is equal to the sampling rate. Also the computational effort is quite low, real time requirements can easily be fulfilled. Methods, based on segmentation, would need much higher computational effort to obtain the same update rate.

V. CONCLUSION

Adaptive autoregressive parameters were used for online analysis of the EEG. They were used in a BCI experiment for calculating fast and reliable feedback. The best online classification result has improved remarkably (from 82% to 94% as correct classified trials) after a few sessions. The idea of the system is, to give the subject feedback as fast and as accurate as possible. It seems that this is a very promising approach.

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REFERENCES

[1] Pfurtscheller, G., Flotzinger, D., and Kalcher, J. (1993), Brain-computer interface—a new communication device for handicapped persons, *J. Microcomp. Appl.*, **16**, pp. 193-299

[2] Pfurtscheller, G., Kalcher, J., Neuper, Ch., Flotzinger, D., and Pregenzer, M. (1996), Online EEG classification during externally-paced hand movements using a neural network-based classifier, *Electroenceph. Clin. Neurophysiol.*, **99**, pp. 416-425.

[3] Wolpaw, J. R., McFarland, D. J., Neat, G. W., and Forneris, C. (1991), An EEG-based brain-computer interface for cursor control, *Electroenceph. Clin. Neurophysiol.*, **78**, pp. 252-259

[4] Wolpaw, J. R. and McFarland, D. J. (1994), Multichannel EEG-based brain-computer communication, *Electroenceph. Clin. Neurophysiol.*, **90**, pp. 444-449

[5] McFarland, D. J., Neat, G. W., Read, R. F., and Wolpaw, J. R. (1993), An EEG-based method for graded cursor control, *Psychobiol.,* **21**, pp. 77-81

[6] Flotzinger, D., Pfurtscheller, G., Neuper, Ch., Berger, J., and Mohl, W. (1994), Classification of non-averaged EEG data by learning vector quantization and the influence of signal preprocessing, *Med. Biol. Eng. Comput.,* **32**, (5), pp. 571-576

[7] Kalcher, J., Flotzinger D., Neuper, Ch., Gölly, S., and Pfurtscheller, G. (1996), Graz Brain-Computer Interface II - Towards communication between humans and computers based on online classification of three different EEG patterns, *Med. Biol. Eng. Comput.,* **34**, pp. 382-388

[8] Priestley, M.B. (1981), *Spectral Analysis and Time Series*. Academic Press, London.

[9] Widrow, B. and S.D. Stearns (1985), *Adaptive Signal Processing*. Prentice Hall, Englewood Cliffs, NJ.

[10] Haykin, S. (1986), *Adaptive Filter Theory*. Prentice Hall, Englewood Cliffs, NJ.

[11] Schloegl, A., Flotzinger D., Pfurtscheller G. (1997), Adaptive autoregressive modeling used for single-trial EEG classification, *Biomedizinische Technik* (submitted)