Discriminance Analysis of Postural Sway Trajectories with Neural Networks

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Abstract

Posturography is widely used for quantitative assessment of balance control function in patients with vestibular dysfunction. The objective of this study was to investigate whether the postural control of normal subjects is influenced by a medium dose of alcohol. 51 young volunteers without known vestibular diseases examined four 40-seconds trials on a fixed surface. Trials were completed under two conditions: eyes closed / opened and before / 40 minutes after consumption of 32 grams of alcohol. The relatively complex time series of the measured center-of-pressure (COP) were analyzed with several methods of spectral analysis, but no clear visible differences depending on the conditions were found, because of large interindividual differences. Estimated spectral power densities of these time series were used as neural network input data. We compare the performance of five types of different classification methods: Learning Vector Quantization, Support Vector Machines, Self-Organizing Maps, Growing Cell Structures and k-Means and show that the first two network types performed best. Validation investigations show that mean test errors of 4.2 ± 2.2 % are obtainable. Results suggest that changes in postural control under the influence of alcohol can be better quantified by autoregressive spectral estimation and by using band averaging over the whole frequency axes. Posturography analyzed by neural networks is a sensitive method for detection of small influences on the postural control system.

Keywords: Classification, Posturography, Support Vector Machines, Learning Vector Quantization, Self-Organizing Map, Growing Cell Structures, k-Means, Spectral analysis

1. Introduction

Posturography is widely used for quantitative assessment of balance control function, especially in patients with vestibular dysfunction [1-6]. Another field of application is the influence of alcohol on balance, which is readily observable in acute cases.
Alcohol is known to have effects on both static and dynamic balance control and is leading to an inability to coordinate postural and voluntary activity [7]. Furthermore, it was found that intoxicating amounts of alcohol significantly prolonged the latency and reduced the amplitude of long-latency muscle responses and can lead to destabilization sufficiently to fall during the test if the eyes are closed.
Ahmad et al. [8] showed that the estimated total number of lifetime alcoholic drinks is positively correlated with antero-posterior sway spectral power in the 2 - 4 Hz and 4 - 6 Hz frequency bands under the condition of closed eyes.

Even in the presence of modest blood alcohol levels the balance is shown to be impaired [8]. The objective of the present study was to investigate whether postural control of normal young subjects is influenced by a medium dose of alcohol.

2. Experiments

51 young volunteers without known vestibular diseases were examined under requirements of the Romberg test, a standard diagnosis test in neurology and otorhinolaryngology. Each subject examined two 40-seconds trials on a fixed surface under the conditions: eyes opened and eyes closed.

Immediately after the first two trials 0.66 grams of alcohol per kilogram body weight were given to each subject as a mixed drink of vodka (40 % vol.) and orange juice to achieve a blood alcohol level of approximately 0.1 % after twenty minutes. All subjects were university students with some experiences in alcohol consumption. They didn't know the given amount of pure alcohol and described the degree of alcohol consumption as moderate.

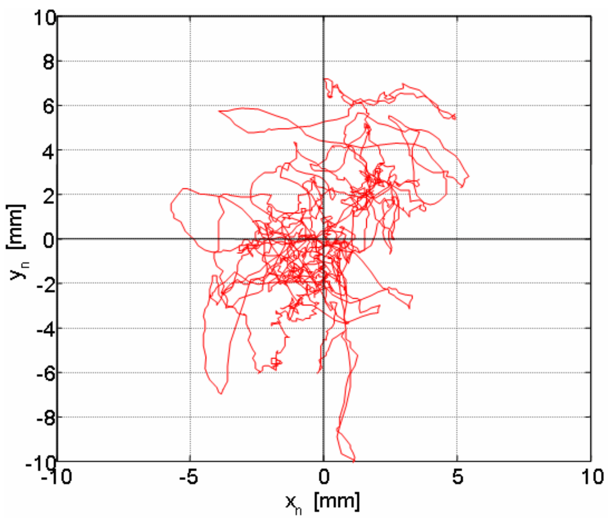

Figure 1: Stabilogram of one subject 40 min after intake of alcohol.

Twenty and forty minutes after consumption further trials were examined under the same two conditions. In the following we report on the results of trials after 40 minutes, because subjectively reported culmination point was between 30 and 45 minutes after intake and discrimination analysis succeeded much more between baseline trials and trials after 40 minutes. Each trial had a length of 40 sec.

3. Analysis

Subjects body movements cause dynamic changes of their center of gravitiy and as a consequence the center of foot pressure (COP) is changing dynamically. The coordinates of COP in antero-posterior (ap) and medio-lateral (ml) directions were measured by a platform consisting of four force sensors and were sampled with a rate of 50 Hz.

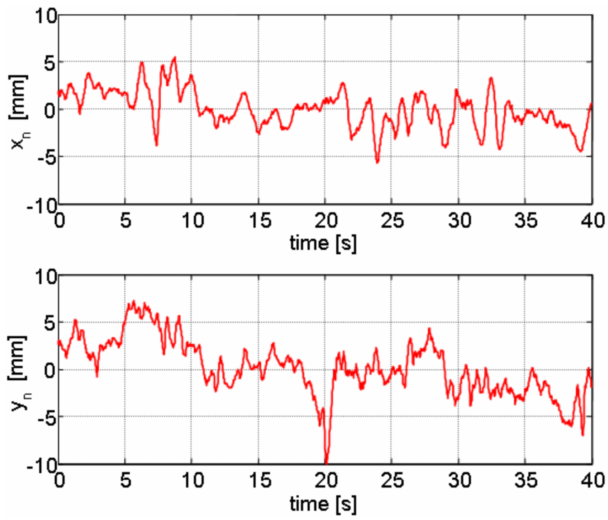

Figure 2: Time series of antero-posterior (y) and medio-lateral (x) coordinates of center-of-pressure (COP).

The bivariate representation of ap- and ml-coordinates of COP is called stabilogram (Fig. 1) and is often used for visual scoring in clinical examinations. The relatively complex time series of ap- and ml- coordinates of COP (Fig. 2) were analyzed by spectral power density estimation. Four different methods were applied [9]:

1.) periodogram method based on discrete Fourier transform (DFT),
2.) autoregressive modelling based on the Burg method (AR),
3.) weighted overlapped segment averaging (WOSA), often called Welch's method, and
4.) multi taper method (MTM).

The periodogram method, which calculates the squared magnitudes of the complex values of amplitude densities obtained from DFT, is under criticism of many authors. For stochastic processes the variances of power densities and their values are in the same order (relative errors of 100 %).

Therefore, variance reduction methods like WOSA are recommended. WOSA estimates the power densities in many overlapping subsegments and averages them. One has to adjust the length of

subsegments and their degree of overlapping. Many small subsegments are good for variance reduction, but with smaller segment length the spectral resolution is lowered and the bias due to leakage is increased. This fact is called the bias variance trade-off of spectral estimation.
The MTM reduces variance by using multiple orthogonal tapers with good leakage properties. It can be shown, using bounds for bias, variance and resolution, that, if a WOSA spectral estimator and a MTM estimator are fixed so that two of the three bounds are identical, the remaining bound favours the MTM estimator [9]. A free adjustable parameter of MTM is the product of effective bandwidth and taper length.
AR methods assume a filtered white noise process as a model of signal generation. Empirical investigations on sample data demonstrated a better localisation of spectral lines and a better discrimination of neighboured spectral lines [10]. AR methods are parametric methods. Criteria for estimation of their model order fail in case of electroencephalographic signals [10]. Here, we varied the model order as a free parameter.

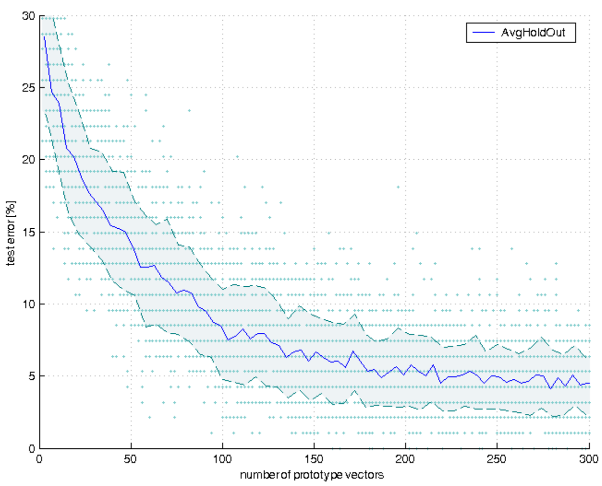

Figure 3: Classification method OLVQ1, mean test errors vs. number of prototype vectors.

Regularly, averaging in frequency bands is done, because of the resulting large amounts of components of spectral power densities and because of their high variances, which are typically for biomedical signals as realizations of random processes. The adjustable parameters of this step are lower and upper cut-off frequency f_L and f_U respectively and the band width Δf. The range between f_L and f_U is equidistantly divided with step size Δf.

The band averaged power densities are the components of input vectors for the classification methods. If n is the number of frequency bands between f_L and f_U, then we have an n-dimensional input space.
Among the following classification methods, with which we have experiences and tested implementations, the best method is selected empirically taking the mean test error into account:

1.) Learning Vector Quantization (LVQ), with variants [12]
2.) Support Vector Machines (SVM) with Gaussian kernel function [13]
3.) Self-Organizing Maps (SOM), calibrated, with modification supervised [15]
4.) Growing Cell Structures (GCS), calibrated, with modification supervised [14]
5.) k-Means (kM), calibrated, with modification supervised [16]

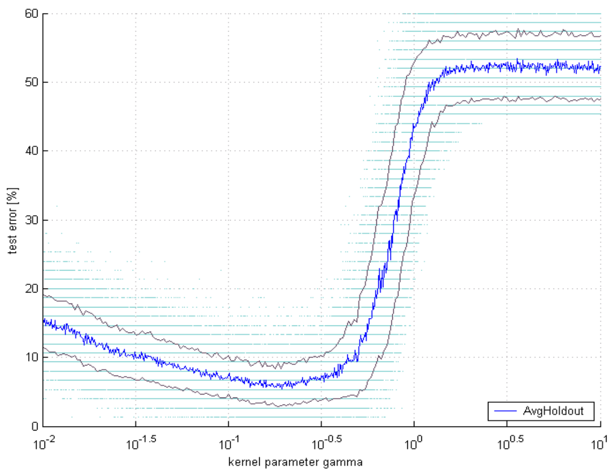

Figure 4: Classification method SVM, mean test errors vs. parameter gamma of RBF kernel function.

4. Results

An important parameter of our classification methods, except SVM, is the number of prototype vectors. Variation of this parameter causes rapidly falling test errors until a specific level of saturation is reached (Fig. 3). At the point where significant error decreases are ending, the optimal number of prototype vectors is found. Standard deviations of test errors occur for three reasons:

1) The data set is randomly partitioned into test and training set during k-fold hold-out, a method of cross validation,

2) The prototype vectors are initialized randomly data-driven,
3) Training samples are applied randomly.

For SVM reasons 2) and 3) are not true. For this method the decision, which type of kernel function has to be used, is important and has to be done empirically, because criteria do not exist [11]. In the present analysis best results were obtained with Gaussian kernel functions. An important parameter of this kernel is gamma, the magnitude of influence of the support vectors. In a semilogarithmic plot test errors are gradually falling, and shortly after their minimum they are rapidly increasing (Fig. 4).

method	E_{TEST} [%]	f_L [Hz]	Δf [Hz]	f_U [Hz]	sl [s]
DFT	8.2 ± 4.1	0	2.5	25	10
AR	4.8 ± 3.5	0	1.3	25	8
WOSA	8.4 ± 3.7	0	0.2	10	7
MTM	6.3 ± 3.4	0	2.3	15	8

Table 1: Estimated minimum of mean test errors and related empirically estimated optimal parameters of averaging in frequency bands and of segmentation. Classification method was OLVQ1.

Other parameters, like those of pre-processing and spectral estimation, are estimated in the same manner. The resulting optimal values show differences depending on the estimation method (Tab. 1), especially the band width and the upper cut-off frequency. Best results were obtained using autoregressive modelling for spectral estimation. The free parameter of AR, the model order, was also estimated by searching for minimal test errors and was found between 8 and 15. AR estimation requires the whole frequency axis, from DC until Nyquist frequency, and averaging in 20 frequency bands seems to be optimal. Each band should have a width Δf of 1.3 Hz; that means that each band contain 10 frequency bins of 0.125 Hz resulting of the optimal segment length sl of 8 s.

All mentioned parameter estimations were done using OLVQ1, a LVQ neural network with adaptive learning rates for each neuron [12]. The question arises if alternative classification methods could perform better. In comparison to unsupervised methods (GCS, SOM, kM) supervised methods (LVQ, SVM) resulted, as expected, in lower mean training and also in lower mean test errors (Tab. 2). As expected, training errors were lower than test errors, because classificators perform better on data which were presented than on those which were never presented during training.

Method	E_{TRAIN} [%]	E_{TEST} [%]
LVQ1	0,8 ± 0,7	4,8 ± 2,7
LVQ2.1	0,8 ± 0,7	4,9 ± 2,6
LVQ3	0,8 ± 0,7	4,8 ± 2,6
OLVQ1	0,2 ± 0,3	4,2 ± 2,2
SVM	0,0 ± 0,0	4,3 ± 2,4
kM	6,9 ± 1,7	16,8 ± 4,4
kM, sv	0,3 ± 0,9	8,9 ± 3,3
SOM	8,9 ± 0,6	13,3 ± 1,7
SOM, sv	1,4 ± 0,6	9,1 ± 3,4
GCS	2,9 ± 1,2	11,2 ± 5,0
GCS, sv	0,3 ± 0,4	8,8 ± 4,4

Table 2: Mean and standard deviation of training errors and test errors for different classification methods. Optimal parameters were selected empirically.

The modification „supervised“ (sv) of all unsupervised methods (Tab. 2) uses the class number (label) as a further component of input vectors, but only during training.. Though the influence of this modification on distance calculation is low, the methods are able to adapt better leading to lower training errors. It is noteworthy that also the test errors are lowered significantly, though during test this modification can not be used. We have no clear interpretation for this performance increase. However, mean test errors of sv modification are twice higher than mean test errors of unsupervised methods. Among the supervised methods OLVQ1 and SVM with Gaussian kernel function performed best.

5. Conclusions

Posturography is shown to be sensitive to differences in balance control functions due to medium doses of alcohol. The results suggest that these differences can be better quantified by autoregressive spectral estimation and by using band averaging over the whole frequency axes. Among five different classification methods with several modifications Support Vector Machines with Gaussian kernel function and Optimized Learning Vector Quantization performed best. For biomedical applications, where most of the signal generating processes are covered by other processes, mean test errors of lower than 5 % are seldom.

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