Using Postural Control System Measures to Detect Hypovigilance

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ABSTRACT

Posturography is a method to assess the postural control system quantitatively providing the possibility for testing vigilance. In this paper we present pilot experiments and analysis investigating the discriminatory abilities of posturography. A total of 10 young adults participated in postural assessment within a study with extended time awake. Acquired measurements were assigned to two classes “vigilant” and “hypovigilant” according to subject’s continuous time-since-sleep (TSS). Two features sets were extracted from posturographical recordings. In time domain 7 kinds of features from other authors were extracted, including measures of sway velocity and sway area. In spectral domain features were extracted by estimating power spectral densities and subsequent averaging in equidistant spectral bands. In addition to static feature extraction this paper introduces analysis of temporal dynamics within the features of both domains. The ability to discriminate between both classes “vigilant” and “hypovigilant” was evaluated in terms of mean test set errors estimated using 25-fold delete-d cross validation. Different algorithms of computational intelligence including artificial neural networks (ANN) and Support-Vector Machines (SVM) were applied. SVM using Gaussian kernel functions performed best with achieved mean test set error rates of 9.0 ± 4.2 %.

Author Keywords

Posturography, Vigilance, Support-Vector Machines, Computational Intelligence, LSTM.

ACM Classification Keywords

I.5.4 Pattern Recognition: Signal Processing

INTRODUCTION

Posturography is a method of quantitative balance assessment and is used as a diagnostic tool in Neurootology. Posturography measures body sway during sitting or standing. For the latter subjects are instructed to stand upright and remain as motionless as possible. The center of pressure (COP) is calculated utilizing a three- or four-point force sensor platform.

Data analysis quantifies features of the medio-lateral and the antero-posterior components of the COP time series (Figure 1). It has been shown, that both components are impaired by hypovigilance [1, 2]. Therefore, posturography is a new candidate for vigilance assessment which may be cost-efficient, short-lasting, mobile, and easy-to-administer. Recent studies in our lab resulted in relatively high error

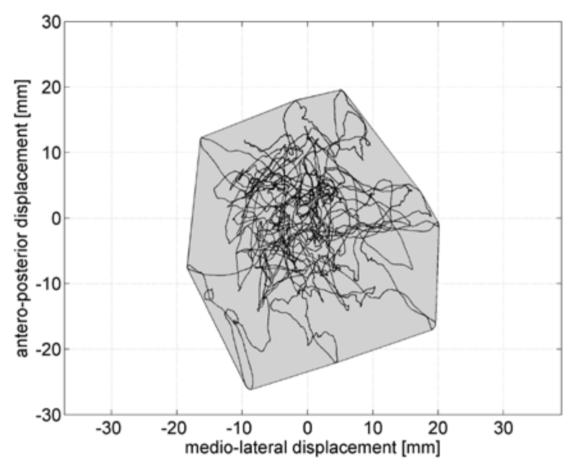

Figure 1. Stabilogram recorded after 14 hrs of continuous time awake under EC condition. Test duration was 120s. The gray polygon indicates the area of the convex hull – one of the utilized time-domain features.

rates when classifying between two extremes: "vigilant" vs. "hypovigilant" [3]. One possible explanation may be the kind of data analysis. For each signal segment a set of different features were extracted. But it was not asked whether temporal dynamics between feature sets of different segments exist. The application of Recurrent Neural Networks (RNN), for example Long Short-Term Memories (LSTM) [4], provides means to answer this question.

Long Short-Term Memory

RNN are ANN characterized by feedback connections between artificial neurons. These connections conduct output variables from one neuron to its neighbors' and predecessors' inputs [5]. In contrast to non-RNN, they are able to process sequences of feature vectors such that the temporal localization of feature characteristics within the sequence gains relevance. RNN are capable to adapt to temporal dynamics within the input sequences. LSTM are trained by a variant of Real-Time Recurrent Learning [4].

An alternative approach is the application of Evolutionary Strategies to adapt input weights of network cells [6]. Schmidhuber et al. [6] demonstrated that combinations of RNN with multivariate output (Fig. 2) with non-linear classifiers have an improved ability to generalize a sub-symbolic temporal memory in the feature space.

METHODS

Study Design

In this contribution a dataset of a partial sleep deprivation study is processed. A total of 10 young and healthy adults volunteered to participate in postural assessment. Posturography was performed during morning hours (10:00-12:00AM) and during eight test runs, hourly between 8:00PM and 4:00AM.

Each test run consists of two conditions. The first trial was performed with eyes opened (EO), focusing a marker on the opposing wall. The second test run was performed with eyes closed (EC) disabling the visual feedback to human balance control. This trial is more demanding and may therefore be sensitive to performance decrements at an earlier stage. Both trials lasted 120 seconds. Subjects were instructed to stand as motionless as possible and to maintain a uniform, practiced upright pose with both feet on the ground.

Pre-Processing

Samples were divided into two classes. The first class ("vigilant") contained test runs of the morning (time-since-sleep < 5 hours) and the second class ("hypovigilant") contained test runs of the late night (time-since-sleep > 14 hours).

During segmentation recorded data is split into non-overlapping segments. Using only the first segment it is possible to simulate different test durations. The segment length was optimized empirically regarding the achieved

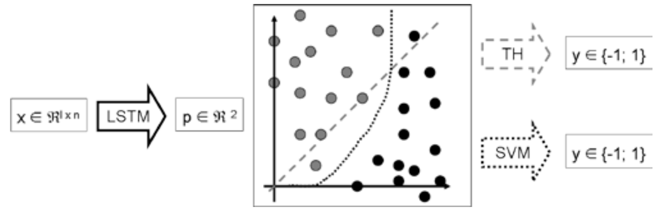

Figure 2. Signal Processing Chain: feature sequences of *l* elements consisting of *n* features each are mapped to a two-dimensional space by LSTM. For linear decisions (TH, dashed line) classificiation errors may occur. Non-linear classifiers (SVM, dotted line) can adapt to more complex distributions.

mean test set error estimated via 25-fold delete-d cross validation [7]. The optimal segment length obtained this way is an indication for the required test duration.

Feature Extraction

In time domain methods utilized by several authors were applied, including, but not limited to amplitude range, measures of velocity and of sway area. In total 32 features were extracted.

In spectral domain power spectral densities have been estimated using Weighted Overlapped Segment Averaging (Welch's method). Estimated power spectral densities have been averaged in equidistant spectral bands. Band averaging parameters are lower and upper cut-off frequency, and band width. They were empirically optimized in terms of lowest test set errors. The number of features varies depending on band averaging parameters.

In addition to full-segment feature extraction a sliding window feature extraction was implemented resulting in sequences of feature vectors. The window size and the percentage of overlapping were both optimized empirically regarding the achieved test set error rates.

Classification

Different methods of computational intelligence have been applied in order to find generalized discriminant functions. We applied Fisher's Linear Discriminant Analysis (LDA), k-Nearest Neighbor (kNN), Learning Vector Quantization (LVQ), Long Short-Term Memories (LSTM), and Support Vector Machines (SVM). Free parameters of these methods were optimized empirically in analogy to feature extraction. The outcomes of sliding window feature extraction (LSTM, SVM_{window}) were compared to the outcomes of static approaches (LDA, kNN, LVQ, SVM).

CONCLUSIONS

This contribution introduces the utilization of sliding window features to Posturography in order to test for vigilance. Preliminary results of a relatively small data set of 10 partially sleep deprived subjects offered that further effort have to be made to improve classification accuracy. In future Evolutionary Strategies should be applied to LSTM

Classifier	Error - Time Domain	Error - Spectral Domain
kNN	**35.8 ± 8.7 %** *k=44*	**18.8 ± 9.0 %** *k=8*
LVQ	**37.1 ± 8.9 %** *n=2*	**19.0 ± 9.0 %** *n=41*
SVM	**22.4 ± 8.3 %** *C=1e3.75 γ=1e-3.375*	**9.0 ± 4.2 %** *C=1e6.375, γ=1e-2.188*
SVM_{window}	**21.6 ± 7.4%** *C=1e0.2813, γ=1e-2.325*	**10.4 ± 6.1 %** *C=1e6.875, γ=1e-4.875*
LSTM	**29.9 ± 8.0 %** *6 blocks, 6 cells each*	**12.0 ±-5.9** *8 blocks, 8 cells each*
LSTM + SVM	**21.1 ± 5.6 %** *6 blocks, 6 cells each* *C=1e1.375, γ=1e-1.75*	**15.3 ± 1.5 %** 8 *blocks, 8 cells each* *C=1e-1.625, γ=1e0*

Table 1. Comparison of classification errors.

training in order to optimize the many free parameters as well as the weight values. Further recurrent methods should be utilized in order to investigate the potential of sequence learning in posturography. Results of Collins et al. [8] indicate that posture in quiet stance is not explainable be random walk models. There are short-term as well as long-term correlations which should by assessable also by sub-symbolic sequence learning.

Despite this dataset being sufficient for first course analysis, the very important questions of inter- and intra-subject variability cannot be examined using this limited dataset. Especially when focusing on intra-subject variability a sufficient large amount of measurements for each subject and different levels of vigilance is necessary. In order to establish posturography as a method for fit-for-duty testing the limitations of this approach regarding inter- and intra-subject variability must be known. In Addition to the classification approach a regression of TSS using posturographical measures is possible [1]. The training of a regression model, e.g. using ANN, can include the whole dataset and is not limited to distinct TSS intervals.

Compared to other vigilance assessment approaches posturography still shows relatively high error rates. Nevertheless it has to be emphasized that these error rates are achieved based on short testing durations. Empirical parameter optimization of segment lengths shows that error rates decrease with increasing test duration. With minor decrements compared to the optimum test durations of 45 seconds seems applicable. Shorter test durations do not only increase the acceptance of the test but also limits test-induced vigilance reducing effects. So far test durations of approximately 10 minutes are common [9, 10].

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