The Compensatory Tracking Task: A Pattern Recognition Based Approach for Classifying Vigilance

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ABSTRACT
In this paper we apply methods of pattern recognition on data of the Compensatory Tracking Task (CTT) in order to classify between two different vigilance states. Ten subjects attended a partial sleep deprivation study. The study design included baseline measurements and measurements of two separate nights. Adaptive signal processing was applied in time and spectral domain. Different classifiers were applied in order to find a generalized discriminant function to discriminate between two pre-defined classes, "vigilant" versus "hypovigilant". The classification performance was evaluated in terms of test set error rates. Results show that best performance was obtained utilizing spectral domain features in combination with Support-Vector Machines. Regarding the test duration results indicate that a test length of six minutes may be sufficient.

Author Keywords
Compensatory tracking task, vigilance testing, signal processing, computational intelligence, support-vector machines.

INTRODUCTION
Although sleepiness is a main cause of accidents at work and in traffic, it is not easy to measure reliably immediate consequences on different performance abilities of a subject. On the one hand sleepiness leads to decrements in attention, cognition and motor control which oftentimes happen suddenly. On the other hand this is difficult to reproduce in test situations. Signal analysis is mainly concerned to continuously measurable decrements and fails in correctly quantifying sudden events. One performance test which continuously demands visuo-motor coordination and which measures performance continuously is the Compensatory Tracking Task (CTT) [1]. The question of this paper is, if the continuously measured cursor-target distances contain information on continuous performance decrements. As a first step, we applied adaptive signal processing and pattern recognition and asked for discriminability in a two-class problem.

MATERIALS

Description of the CTT
The test was executed on a standard personal computer with a trackball as the input device. In the centre of the screen a fixed annulus was presented as the target. The cursor was shaped circularly. The goal of the CTT is to locate the cursor such that the distance of the centre of the cursor to the centre of the target is zero. Only in this case a solid circle is displayed. During the duration of the test the target-cursor-distance is measured continuously at a rate of 12 Hz. The cursor is driven by three virtual forces [1]. A buffeting force calculated as a superposition of six sine functions with randomly initialized phase angles acts with limited dynamics and is still not predictable by the user. A second force acts radially like a Coulomb distraction force. The user interactions generate the third component. Even alert and trained subjects don't succeed in trying to keep the performance measure at zero.

Subjects and Study Design

Students of the University of Applied Sciences Schmalkalden were recruited for this study. They had to fill-out three questionnaires (PSQI [2], D-MEQ [3] and SSQ [4]). Several criteria for inclusion or exclusion were checked based upon these questionnaires. Ten subjects were selected randomly. Their age ranged between 18 and 32 years (mean 24.6 ± 3.7). They were invited to two training sessions. During the two days before experiments all subjects had to wear a wrist actometer to assess main biorhythmical variables and to check adherence to the given sleep-wake schedule. Every subject participated in two experimental nights starting at 8:00PM and finishing at 4:00AM, each night was divided into 8 hourly sessions. Within one session 6 different kinds of tests had to be performed; their order was randomized. This contribution focuses on presentation and discussion of CTT results.

METHODS

Pre-Processing

The x- and y-components of the cursor-target distance (r_t) and of the current cursor position (x_t, y_t) were analyzed. Adaptive segmentation was performed. Their parameters were optimized empirically [5]. Samples of baseline experiments where time since sleep (TSS) was lower than five hours were labeled to class # 1 ("vigilant") whereas samples of the late night (TSS > 18 hours) were labeled to class # 2 ("hypovigilant").

Feature Extraction

Signal Analysis of recorded performance time series were performed in time and spectral domain. In the time domain 29 features were extracted of each segment of the 3 time series (x_t, y_t, r_t). They are used by other authors as well [1]. Power spectral densities are usually utilized as features in time series analysis. We estimated them by WOSA (Weighted Overlapped Segment Averaging) in order to get low variances at the cost of bias and of spectral resolution. At the same side of "costs" are the consequences of band averaging which further reduces estimation variance. The three parameters (lower / upper cut-off frequency and bandwidth) were optimized empirically [6] and resulted in 0.12 Hz, 3.16 Hz and 0.76 Hz, respectively.

Classification

Three different algorithms were compared: Learning Vector Quantization (LVQ), k-Nearest-Neighbor (kNN) and Support-Vector-Machine (SVM). LVQ is an Artificial Neural Network which training stage is relatively fast. Thus it is appropriate to empirical parameter optimizations. The main LVQ parameter to be optimized is the number of neurons [6]. kNN is a non-parametric method of statistical pattern recognition, well-known for decades. The algorithm is very simple, but is not able to perform adaptation and has relatively high computational costs. The parameter k is to be optimized empirically in order to regularize the piecewise linear separation function of kNN. SVM is a class of high-performance classification analysis. It is able to regularize between empirical classification error minimization and structural risk optimization. SVM solves the classification task through implicit transformation to high-dimensional space. It belongs to nonlinear discriminant analysis and is an important method in Computational Intelligence. SVM classification performances were validated using leave-one-out scheme. Validation of LVQ and kNN utilized 50-fold delete-d cross validations with test-training ratios of 80:20.

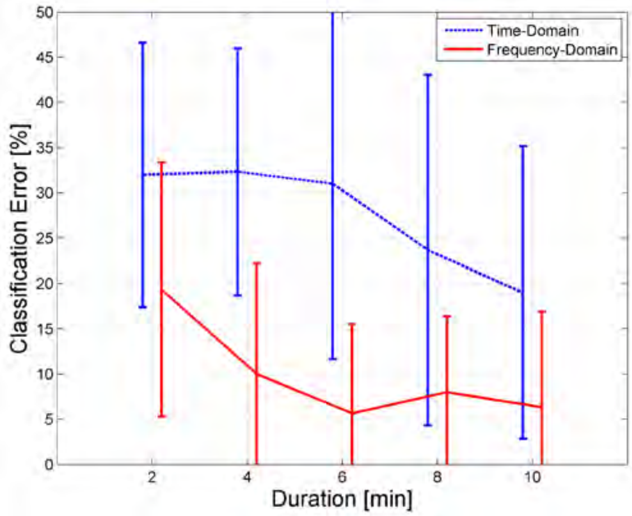

Figure 1. Mean classification errors versus test duration. Features extracted in time domain and spectral domain had been used as input to discriminant analysis utilizing LVQ. Error bars indicate ± 1 standard deviation.

RESULTS & DISCUSSION

Frequency-domain feature sets led to lower classification errors compared to time-domain feature sets. Frequency-domain features showed a minimum in classification error rates at simulated test durations of 6 minutes which is in contrast to time-domain features. Here the minimum was observed at test durations of 10 minutes (Figure 1). Best results are observed using SVM, worst using kNN.

This study gives further evidence that the CTT is able to measure continuous decrements due to operator fatigue. In the future it has to be shown if these results keep stable when sample size is increased. Intra- and inter-subject variability has also to be estimated. Our results indicated that test durations can be reduced to 6 or 4 minutes in future. Further research should also answer the question, if there are single features of the signals which indicate performance decrements.

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