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DATA ANALYSIS OF THE COMPENSATORY TRACKING TASK USING COMPUTATIONAL INTELLIGENCE

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ABSTRACT

Several attempts have been made to assess sleepiness by test procedures within short time. Short-term observations lead to increased uncertainty. On the other hand, methods of Computational Intelligence are known to deal with large variance and limited amount of data which prevents the application of parametric statistics. This contribution aims at improving sleepiness estimation based on the compensatory tracking task (CTT) by the application and optimization of different classifiers. Ten subjects attended a study with extended waking time. During the test duration of ten minutes subjects are instructed to maintain a minimum distance between a disk-shaped cursor and the annular target (screen-center). The obtained target-cursor-distance time series were analyzed in time and spectral domain. Data was assigned to classes according to subject's time-since-sleep (TSS). Different classifiers were applied and compared in terms of highest test set accuracy using 50-fold delete-d validation. With rising TSS classification accuracy increases, indicating that the extracted features are sensitive to sleepiness. The combination of SVM and spectral-domain features resulted in highest values of 96.9 ± 9.5%. Extended experiments need to prove that these results are replicable with a larger group of subjects.

Index Terms - Compensatory Tracking Task, Sleepiness Testing, Signal Processing, Computational Intelligence, Learning Vector Quantization, Support-Vector Machines

1. INTRODUCTION

In our 24/7 society sleepiness is regarded to be a main cause of accidents at work and in traffic. Despite high efforts of several research groups from different fields it is still not easy to measure reliably immediate consequences on different performance abilities of a subject. Sleepiness leads to mostly sudden decrements in attention, cognition and motor control. But it is difficult to reliably reproduce these decrements in test situations. Many different methods to assess sleepiness have been proposed. Among them is the Compensatory Tracking Task (CTT) [1]. The CTT demands continuous visuo-motoric coordination. In contrast to event based approaches like the psychomotoric vigilance task (PVT) [2] the CTT assesses performance continuously. Therefore the methods of adaptive signal analysis in combination with Computational Intelligence are applicable to CTT data. The question of this paper is, if such continuously measured performance data contain information on continuous performance decrements..

2. MATERIALS

2.1. Description of the CTT

The test was executed on a standard personal computer with a trackball as input device. In the centre of the screen a fixed annulus was presented as target. The cursor was shaped circularly as large as the inner area of the annulus. Subjects are instructed to locate the cursor such that the distance of the centre of the cursor to the centre of the target is zero. 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 without being predictable by the user. A second force acts radially intended to obtain a given target-cursor-distance. The user interactions generate the third component. Without any user input the cursor moves freely within a certain circular area surrounding the target. Even trained and alert subjects are challenged when instructed to maintain a target-cursor-distance close to zero.

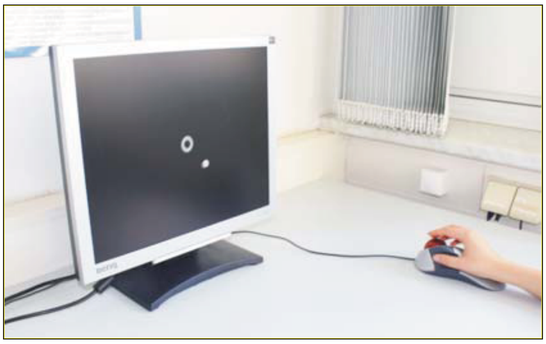

Figure 1 CTT training setup: trackball and computer screen with the target annulus and the cursor.

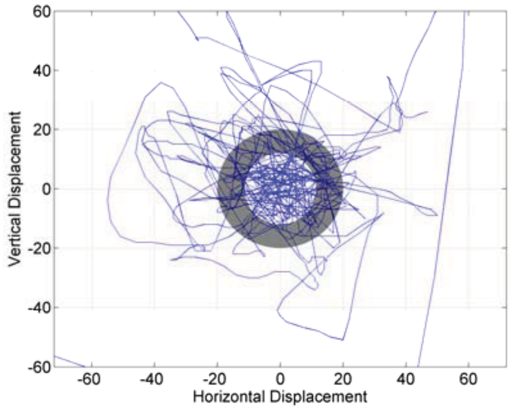

Figure 2 Target and path of the cursor during a 2 minute lasting training session of a trained subject.

Class	Nightly Sessions Included							
#2	1	2						
#3		2	3					
#4			3	4				
#5				4	5			
#6					5	6		
#7						6	7	
#8							7	8

Table 1 Nightly sessions were assigned pairwise to 7 classes.

2.2. Experiments

Students of the University of Applied Sciences Schmalkalden were recruited for this pilot study. During the registration process volunteers completed three questionnaires. The Pittsburgh Sleep Quality Index (PSQI) identifies notable losses of sleep quality [3]. Applicants with questionable sleep quality (PSQI > 7) were rejected. The German translation of the morningness-eveningness questionnaire was utilized in order to identify the chronotype tendency of a person [4]. In order to gain significant performance deficits in the late evening, only subjects with at least a tendency to morningness were selected (D-MEQ > 58). Further criteria for inclusion or exclusion were checked based on a non-standardized questionnaire, e.g. medication.

From the pool of accepted applicants 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 and two baseline sessions. Especially regarding the CTT several training runs are necessary [1]. During both training sessions at least 6 test runs needed to be completed by each subject. Baseline sessions are used as a reference for the data analysis. Therefore these sessions were performed during periods of high alertness. Since the selected subjects tend to an early chronotype a time window between 9:00AM and 12:00AM was chosen.

Two days before experiments all subjects had to wear wrist actometry devices to assess main biorhythmical variables, e.g. sleep onset and offset. Furthermore these devices were used to check the adherence to the given sleep-wake regime. Subjects were instructed to leave bed before 9:00AM. Daytime naps were allowed prior to the experiments in order to have uniform TSS for all subjects. Experiments started at 8:00PM and finished at 4:00AM. The night was divided into 8 hourly sessions. Besides the CTT five other tests, which are not within the scope of this contribution, were performed each hour in randomized order.

3. METHODS

3.1. Pre-Processing & Labeling

From the acquired CTT data the time series of the target-cursor-distance (d_t) and the x- and y- components of the cursor position (x_t, y_t) were extracted.

One major factor of sleepiness is the sleep pressure which rises steadily during waking hours Therefore reference data needed to be obtained during the morning hours. Baseline experiments, where time since sleep (TSS) was lower than five hours, were assigned to class #1 ("very alert"). After the circadian peak in the afternoon subjects move toward their circadian trough resulting in the increasing TSS being the dominant factor of sleepiness [6]. In order to show that subject's performance during the CTT is affected by TSS the classification performance was evaluated in dependence of TSS. Samples acquired during the night (11 hours < TSS < 19 hours) were assigned pairwise to seven classes (Table 1). This way the number of samples between class #1 and classes #2 to #8 are equal. It was expected that the dissimilarity of patterns between reference data and nightly data increases with increasing TSS. This increased dissimilarity should lead to increased classification accuracy.

3.2. Feature Extraction

Within time domain 29 features were extracted using the x_t, y_t and d_t time series. These include different statistical moments of those time series and their first and second derivations. Another sub-set of features consists of area measures like the area of the convex hull and the area of the encapsulating rectangle. Fig. 1 shows a typical distribution of feature values. On the one hand there is an obvious trend towards increased mean values during the course of the day. On the other hand values scatter largely, indicating complex distributions within the multivariate pattern space.

Within spectral domain 12 features were extracted for each time series (36 features total). Power spectral densities are usually utilized as features in time series analysis. We estimated them using Weighted Overlapped Segment Averaging (WOSA) in order to get low variances at the cost of bias and reduced spectral resolution. Subsequent band averaging has the same negative consequences but is reducing estimation variance further. The three parameters (lower / upper cut-off frequency and bandwidth) were optimized empirically [7] and resulted in 0.12 Hz, 3.16 Hz and 0.76 Hz, respectively.

3.3. Discriminant Analysis

Three different algorithms were compared: Learning Vector Quantization (LVQ), k-Nearest-Neighbor (kNN) and Support-Vector Machines with Gaussian kernel functions (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 prototype neurons [7]. kNN is a non-parametric method of statistical pattern recognition, well-known for decades. The algorithm is simple, but not able to perform adaptation and may have 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 method with a superior classification performance, as proven in different benchmarks. It is able to regularize between empirical error minimization and structural risk optimization. SVM solves the classification task utilizing implicit transformation to the higher-dimensional feature-space. It belongs to nonlinear discriminant analysis and is an important method in Computational Intelligence. For all methods a 50-fold delete-d cross validation (test-training ratio of 80:20) was utilized.

4. RESULTS

4.1. Classifier Comparison

It was expected that best results are to be obtained when discriminating between class #1 and #8 since the difference in TSS is maximal in this case. Using this setup SVM shows highest classification accuracy. The rates of LVQ and kNN were 3% to 15% lower (Table 2). All results have a high standard deviation of at least 9.5%. One possible reason for these high values is the limited sample count of 40 patterns per problem. Removing 8 out of 40 patterns biases clusters in the pattern space more likely than removing 80 out of 400 patterns.

4.2. Influence of TSS

Since the computational effort of SVMs is high, only LVQ results for the other classification problems were available so far (Table 3, Figure 3). Due to the high standard deviations the statistical significance of differences in the achieved mean accuracies is questionable. Nevertheless a similar trend can be observed in both time and spectral domain. With increasing TSS classification performance increases, indicating that the dissimilarity between the reference data and the “sleepy” data increases.

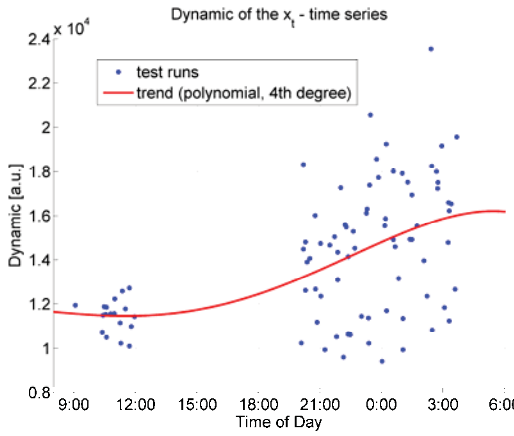

Figure 1 Distribution of one single time domain feature. During baseline condition feature values are quite compact. With increased TSS mean values shift and variance increases. Similar characteristics can be observed for all time-domain features.

Classifier	Time Domain	Spectral Domain
kNN	78.0 ± 17.0 k = 1	91.5 ± 11.3 k = 5
LVQ	80.7 ± 15.6 #neurons = 6	93.7 ± 10.6 #neurons = 21
SVM	93.7 ± 12.3 C= 10^6.5 γ = 10^-12.375	96.9 ± 9.5 C= 10^1 γ = 10^-1.5

Table 2 Mean and standard deviations (SD) of classification accuracy for discriminating between class #1 and #8 using different classifiers.

Problem	Time Domain	Spectral Domain
#1 vs #2	69.1 ± 14.4	83.2 ± 11.9
#1 vs #3	65.6 ± 14.7	84.5 ± 13.0
#1 vs #4	69.7 ± 12.1	83.7 ± 14.8
#1 vs #5	73.4 ± 15.3	88.7 ± 11.0
#1 vs #6	77.1 ± 14.4	93.6 ± 8.2
#1 vs #7	78.1 ± 13.7	93.2 ± 9.9
#1 vs #8	80.7 ± 15.6	91.9 ± 9.9

Table 3 Mean and standard deviations of classification accuracy for discriminating between class #1 and classes #2 to #8 using LVQ.

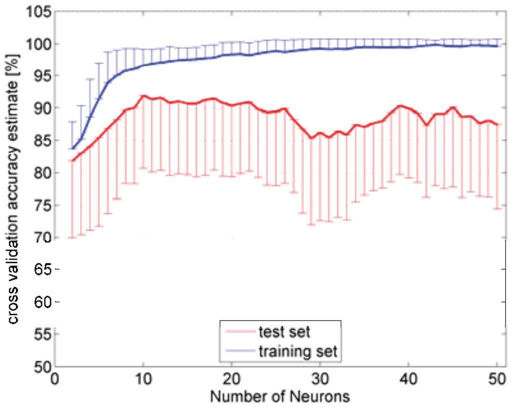

Figure 2 LVQ model complexity parameters are optimized empirically. Errorbars indicating ± 1 SD are shown asymmetrically in order to preserve readability.

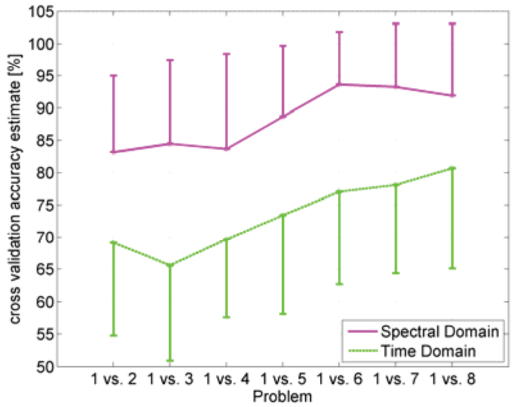

Figure 3 Despite questionable statistical significance results show a trend indicating that increased TSS leads to increased classification accuracy.

5. CONCLUSIONS

This study gives further evidence that the CTT is able to measure continuous decrements due to operator sleepiness. The results of the class #1 vs. class #8 problem shows that the introduced pattern recognition chain is able to discriminate between two strongly different levels of sleepiness. With decreased sleepiness the classification accuracy decreases indicating that the dissimilarity within in the data originates in the effects of sleepiness. Therefore it can be summarized that the CTT is sensitive to the effects of sleepiness and is therefore applicable to assess operator's fitness-for-duty based upon reference data.

This contribution didn't examine the effects of data fusion on the feature level, which was successfully applied for other related applications [8]. With feature fusion the question of feature reduction and feature combination gains increased relevance and needs to be evaluated.

Furthermore it has to be shown that the findings of this contribution are replicable with an increased number of subjects. Especially intra- and inter-subject variability needs to be estimated. When inter-subject variability is too high the CTT can only be used in "closed" environments where reference data for each person is available, but not for e.g. roadside testing. Nevertheless if the intra-subject variability is acceptable low CTT can be regarded as a method for fit-for-duty testing.

6. REFERENCES

[1] S. Makeig and M. Jolley, "COMPTRACK: A compensatory tracking task for monitoring alertness", Technical Document 96-3C, Naval Health Research Center, San Diego, 1996.

[2] D.F. Dinges and J.W. Powell, "Microcomputer analysis of performance on a portable, simple visual RT task sustained operations", Behavioral Research Methods, Instrumentation and Computers, 17, pp. 652-655, 1985

[3] D.J. Buysse, C.F. Reynolds, T.H. Monk, S.R. Berman and D.J. Kupfer, "The Pittsburgh Sleep Quality Index", Psychiatry Res 28, pp. 193-213, 1989.

[4] J.A. Horne and O. Östberg, "A questionnaire to determine morningness-eveningness in human circadian rhythms", Int J Chronobiol 4, pp. 97-110, 1976.

[5] T. Akerstedt, "Subjective and objective sleepiness in the active individual", International Journal of Neuroscience, 52, pp. 29-37, 1990.

H.P.A. Van Dongen and D.F. Dinges, "Circadian rhythms in sleepiness, alertness, and performance", In: M.H. Kryger, T. Roth, W.C. Dement (eds), Principles and Practices of Sleep Medicine, Saunders, Philadelphia, pp. 435-443, 2000

[6] D. Sommer, Charakterisierung des Mikroschlafs mit neuroinformatischen Methoden, PhD Thesis (in German), Shaker Press, Aachen, 2009

[7] M. Golz and D. Sommer, "Automatic knowledge extraction: fusion of human expert ratings and biosignal features for fatigue monitoring applications", In: D.P. Mandic, M. Golz, A. Kuh et al. (eds), Signal Processing techniques for knowledge extraction and information fusion, Springer, New York, pp. 299-316, 2008