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COMPUTER SCIENCE AND AUTOMATION

COMPUTER SCIENCE MEETS AUTOMATION

VOLUME I

Session 1 - Systems Engineering and Intelligent Systems

Session 2 - Advances in Control Theory and Control Engineering

Session 3 - Optimisation and Management of Complex Systems and Networked Systems

Session 4 - Intelligent Vehicles and Mobile Systems

Session 5 - Robotics and Motion Systems

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Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

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2 Advances in Control Theory and Control Engineering

52^{nd} Internationales Wissenschaftliches Kolloquium
Technische Universität Ilmenau
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D. Sommer / M. Golz

Feature Reduction for Microsleep Detection

Abstract. In stages of extreme fatigue, e.g. while car driving, dangerous microsleep events may occur. Their detection in spontaneous biosignals still poses a challenge. For this purpose it is necessary to analyze signals with high temporal dynamics, like the brain and eye electric activity. From both types of measurements the Power Spectral Densities were estimated and were subsequently reduced by five different methods. Their performances were evaluated empirically in order to get lowest errors for the detection of microsleep events. The detection was realized by Computational Intelligence methods. It turned out that feature reduction performs best when averaging in many small spectral bands or in flexible spectral bands was utilized. Their free parameters were optimized by genetic algorithms. The Support Vector Machine with RBF kernel function established as best performing classification tool.

INTRODUCTION

One of the most important human factors causing accidents is operator fatigue and loss of attention. Their portion among all accidents is estimated as 15 to 20 % and is exceeding in this respect the importance of alcohol and drugs [1]. In stages of extreme fatigue dangerous microsleep events (MSE) may occur. MSE are defined as short intrusions of sleep under the demand of sustained attentiveness. Their detection in spontaneous biosignals still poses a challenge.

In contradiction to the evaluation of fatigue where a wide range of different signals are available, it is difficult to get suitable signals which immediately reflect ongoing MSE on a second by second basis. Mostly, measurements of brain electric and of eye movement activity are used, which are featured by high temporal resolution. Disadvantageously, they are non-contactless and are corrupted by large noise which is originated by other simultaneously ongoing processes. This leads to more or less extensive signal processing and pattern recognition.

It has been shown that the empirical error of recognition sensitively depends on several parameters of the preprocessing, the feature extraction and the classification stages [2]. Considerable improvements can be gained if different signal sources are fused on the feature level [3]. Furthermore, it turned out that feature extraction in the spectral domain is most successful compared to methods in the state space or time domain [3]. Therefore, we here report only of feature extraction and subsequent reduction in the spectral domain.

The common way of feature reduction during EEG analysis is band averaging. The Power Spectral Densities (PSD) are averaged in four or more frequency bands. Their definition is not fixed and varies to some extend between different authors. Typical values are 0.5 – 4.0 Hz (delta band), 4.0 – 8.0 Hz (theta band), 8.0 – 12.0 Hz (alpha band) and 12.0 – 30 Hz (beta band) [4]. The question arises if this or other choices are optimal for quantitative EEG analysis, especially when modern Computational Intelligence methods are applied. They do not suffer from the so-called ‘curse of dimensionality’ [5]. In this line, we have established five different cases:

(1) No reduction; all available frequency bins up to the Nyquist frequency are included,
(2) Feature reduction utilizing Principal Component Analysis (PCA),
(3) Feature reduction by averaging in fixed band [4],
(4) Feature reduction by averaging in equidistant bands,
(5) Feature reduction by averaging in arbitrary bands utilizing genetic algorithms.

The outcome of all these methods were applied as input values to Computational Intelligence methods in order to establish a detector for microsleep [6]. The detection accuracy, estimated by the classification error of all feature vectors of the test set, is a useful empirical measure to compare all five cases. For this purpose the widely accepted multiple hold-out validation was used.

EXPERIMENTS

Experiments were conducted in our real car driving simulation lab (Figure 1). 23 young adults took part and each of them finished 7 driving sessions which are repeated every hour between 1 a.m. and 8 a.m. One driving session has a length of 35 minutes. It turned out that the likelihood of occurrence of MSE was gradually increasing due to monotony and fatigue. Fatigue has initially been induced by at least 16 hours without sleep prior to the experiment.
During driving the brain electric activity reflected by the EEG was recorded from seven different locations on the scalp. The eye and eyelid movements reflected by the Electrooculogram (EOG) were recorded from two locations (vertical, horizontal): Both were sampled at a rate of 128 sec^{-1}.

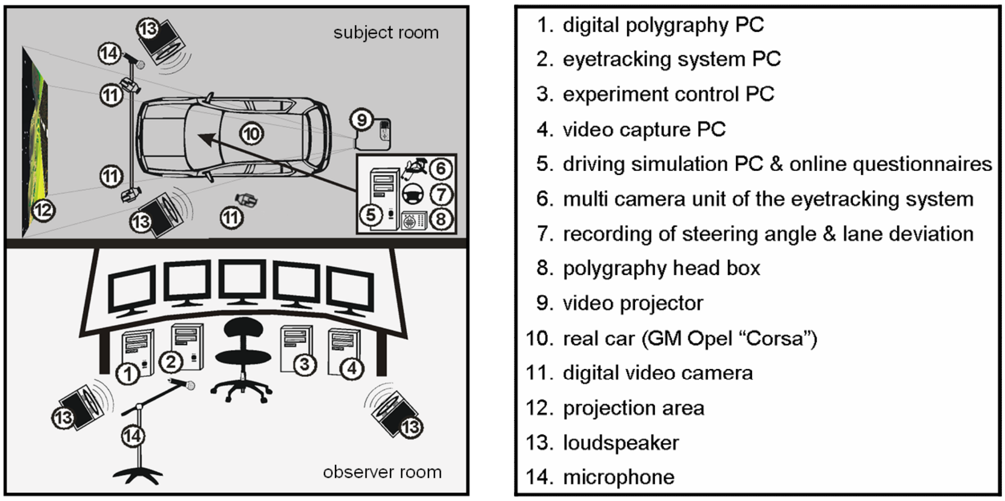

Figure 1: Our laboratory which is specialized for recording of overnight-driving simulations. A real small city car in conjunction with a 3D driving simulation software is utilized to give a monotonic lane tracking task to the subjects. Subject behaviour is video recorded. Also the driving performance and the biosignals of the subject are stored.

MSE are typically characterized by driving errors, prolonged eye lid closures or nodding-off. Towards automatic detection, two experts performed the initial MSE scoring, whereby three video cameras were utilized to record i) drivers portrait, ii) right eye region and iii) driving scene. For further processing, only clear-cut cases, where all the experts agreed on the MSE, were taken into account. Despite providing enough test data to tune our algorithms, the human experts could not detect some of the typical attention lapses, such as the one with open eyes and stare gaze. The number of MSE varied amongst the subjects and was increasing with time of day for all subjects. In all 3,573 MSE (per subject: mean number 162 ± 91, range 11 – 399) and 6,409 non-MSE (per subject: mean number 291 ± 89, range 45 – 442) were scored. Non-MSEs are periods between MSE where the subject is drowsy but shows no clear or unclear MSE. This clearly highlights the need for an automated MSE detection system, which would not only detect the MSE also recognized by human experts, but would also offer a possibility to detect the critical MSE cases which are not recognizable by human experts.

METHODS

Segments of all 9 electrophysiological signals (seven EEG and two EOG channels) were extracted with respect to the observed temporal starting points of MSE / Non-MSE using two free parameters, the segment length and the offset between first sample of segment and starting point of an event. The trade-off between temporal and spectral resolution is adjusted by the segment length and the location of the region of interest on the time axis is controlled by the temporal offset. Both parameters are of high importance and are to be optimized [2]. The variation of the segment offset resulted in a relatively steep error function. An optimal offset value was found to be around -3 sec. In the same way an optimal segment length of 8 sec was found [2]. This means that classification is working best when 3 sec of EEG / EOG immediately before a MSE and 5 sec during ongoing MSE are processed.

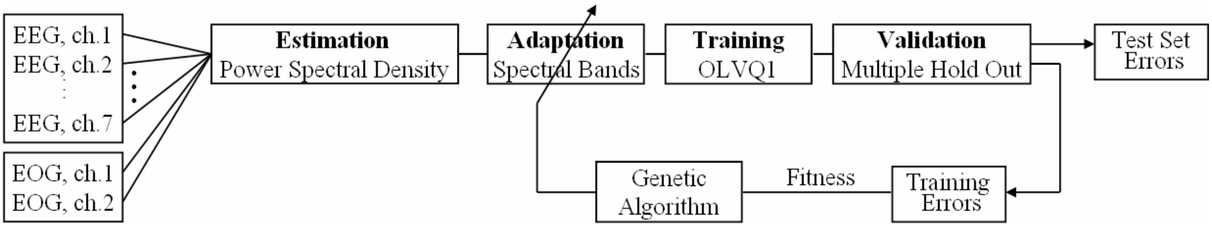

Figure 2: GA-OLVQ1 framework for empirical optimization of band averaging.

After linear trend removal the PSD values were estimated by the modified Periodogram method utilizing Hann windows. Subsequently, the PSD values were scaled logarithmically which has been shown to be important for error diminishing [3]. Now the above mentioned five cases of feature reduction were applied. Each feature vector consisted of 4617 components resulting of sampling in 9 channels at 128 sec^{-1} over a period of 8 sec (case 1). In order to reduce this large amount of components the PCA was utilized (case 2). As a criterion which subspace is optimal the eigenvalues of the covariance matrix were used. Case (3) is the well-known averaging of PSD values in fixed spectral bands. Their cut-off frequencies are mentioned above. This case came out by an extreme reduction from 4617 to 36 (4 x 9) components. In case (4) three free parameters of an averaging in equidistant bands were optimized: lower (f_L) and upper (f_U) cut-off frequency and the width (Δf) of each band. Optimal values were found to be f_L = 0.5 Hz, f_U = 23.0 Hz, and Δf = 1.0 Hz, respectively. In the most flexible case (5) averaging was performed in spectral bands of arbitrary location and width. The training errors of Optimized Learning Vector Quantization (OLVQ1) were used as fitness function of genetic algorithms (GA) (Figure 2) [3]. Genetic representation was fixed to 10 spectral bands, each defined by lower and upper cut-off frequency for each EEG and EOG channel. This resulted in 180 real values (10 x 2 x 9), which were optimized by evolutionary strategy with Gaussian mutation and an averaging crossover method. Usually GA-OLVQ1 optimizations were finished after computation of 300 generations of 256 individuals per population. The variability of the resulting optimal gene expressions was estimated by repeated (100 times) application of all methods to the data set.

All mentioned optimizations were done empirically. We employed mainly Optimized Learning Vector Quantization (OLVQ1) [7] as a robust, very adaptive and rapidly converging classification method. OLVQ1 has at least one further free parameter to be optimized, the number of prototype vectors. During parameter optimization the minimal test error was searched following the cross-validation paradigm of “multiple-hold-out”. Only when utilizing Support Vector Machines (SVM) the paradigm of “leave-one-out” was applied, which is an almost unbiased estimator of the true classification error [8]. In fact, this method is computationally much more expensive than “multiple-hold-out”, but only for the SVM classifier an efficient implementation exists [8]. The SVM applied on the given problem uses the RBF kernel function, because it matches best [6].

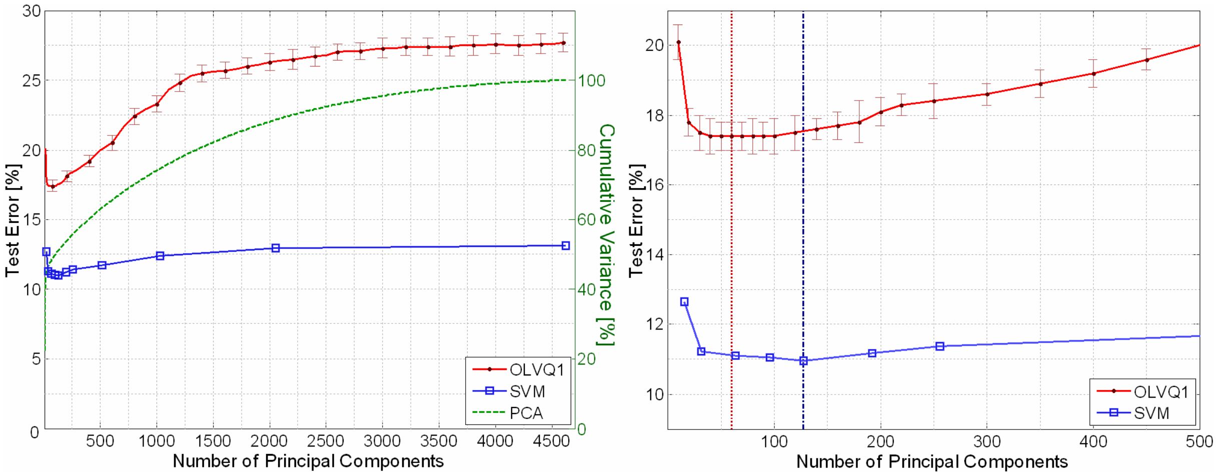

Figure 3: Test set errors of OLVQ1 (dots) and SVM (squares) and the cumulative variance (dotted) versus the number of ranked principal components. Minimal errors were achieved by processing the first 60 and first 128 principal components by OLVQ1 and SVM, respectively (see enlarged view, right). For each sample of the SVM plot separate hyper-parameter optimizations were performed.

Case	Number of Features	OLVQ1		SVM	
		E_{TRAIN} [%]	E_{TEST} [%]	E_{TRAIN} [%]	E_{TEST} [%]
(1) No feature reduction	4617 (513x9)	22.6 ±0.5	27.7 ±0.6	0.0 ±0	13.1 ±0
(2) PCA	60 ¦ 128	10.4 ±0.2	17.4 ±0.4	1.4 ±0	10.9 ±0
(3) fixed band	36 (4x9)	11.6 ±0.2	17.5 ±0.4	4.9 ±0	13.2 ±0
(4) equidistant bands	216 (24x9)	9.3 ±0.1	15.7 ±0.4	0.1 ±0	9.9 ±0
(5) GA-OLVQ1 optimized	90 (10x9)	8.2 ±0.1	14.1 ±0.4	0.1 ±0	9.8 ±0

Table 1: Mean and standard deviation of training and test errors for 5 different cases of feature reduction. Errors were estimated by Multiple Hold-Out and by Leave-One-Out cross validation utilizing OLVQ1 and SVM, respectively.

RESULTS

If all 4617 PSD values are processed, then the classification methods have to adapt a relatively high dimensional decision function. OLVQ1 achieved test set error of 27.7 % in the mean, whereas SVM achieved 13.1 % (Figure 3, Table 1). These results can be outperformed by feature reduction. The Principal Component Analysis (case 2) [9] resulted with minimal errors when not more than the first 3 % of principal components were utilized for classification (Figure 3). OLVQ1 came out by a tremendous decrease down to 17.4 % whereby only the first 60 principal components were needed. In contrast, SVM utilized twice more components (128) to achieve minimal test set errors down to 10.9 % (Figure 3).

Case (3) uses the common way of feature reduction in EEG analysis, namely the averaging of PSD values in fixed spectral bands [4]. Mostly, a relatively coarse split in four bands is applied, as explained above. This leads to 36 features (4 bands x 9 signals). OLVQ1 resulted in lower errors than in case (1) and in nearly same errors than in case (2). SVM came out with no improvements (Table 1). This is not the case with many small spectral bands (case 4). Empirical optimizations of the three free parameters resulted in f_L= 0.5 Hz, f_U= 23.0 Hz and Δf= 1.0 Hz, i.e. 24 band-averaged PSD values for each of the nine signals. Case (5) aimed at improving errors with a fixed number of spectral bands whereby the parameters for each band are optimized empirically. This method is most flexible and resulted best albeit only slightly better than case (4).

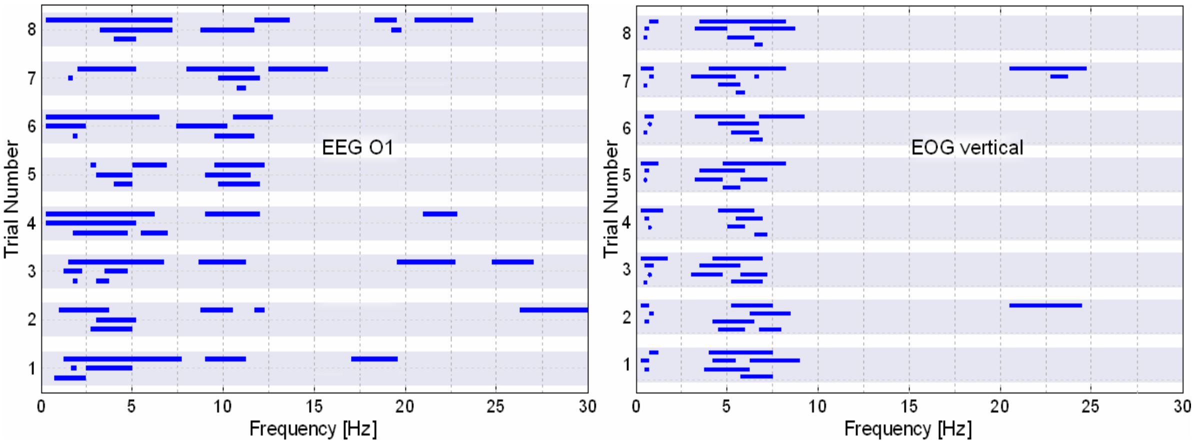

Figure 4: Eight randomly selected genetic representations (out of 100) found for EEG-O1 (left) and vertical EOG (right). Each bar represents both parameters (location and width) of the spectral bands. The plots are limited to 30 Hz while optimizations were performed up to 64 Hz.

The empirical optimizations of case (5) were performed individually for each spectral band, so that overlapping bands and different frequency intervals were found for each signal. These optimizations were repeated 100 times with random initializations of the genetic algorithm. It came out that the band parameters (location and width) varied slightly from run to run. Figure 4 shows 8 randomly selected genetic representations of spectral bands found for two signals (EEG-O1, vertical EOG). The other free parameters of the genetic algorithm, e.g. number of bands, population size and number of generations, were optimized empirically in prior steps.

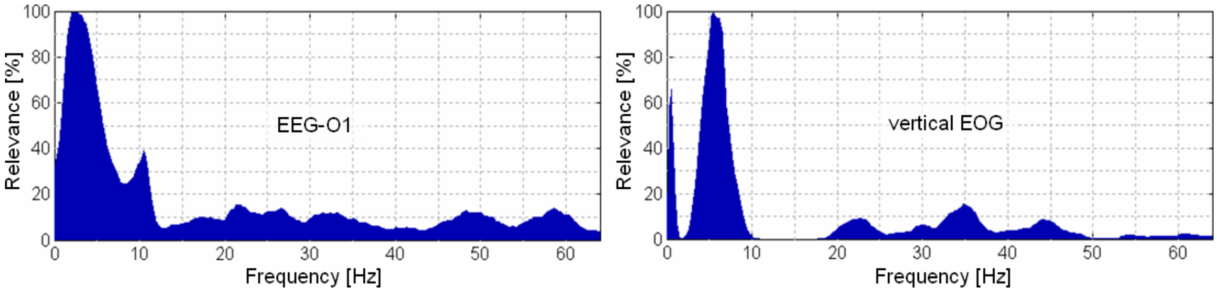

Figure 5: Relevance of frequency selection due to spectral band optimizations for the EEG-O1 (left) and the vertical EOG (right) signal. Results are the outcome of 100 GA-OLVQ1 runs.

In the EEG-O1 signal different bands resulted (Figure 4, left). Overlapping bands occurred mostly in the delta (0.5 – 4 Hz), theta (4 – 8 Hz) and alpha region (8 – 12 Hz), but not in the beta (12 – 30 Hz) and gamma region (30 – 64 Hz). As expected, the outcome for the vertical EOG was different (Figure 4, right). Optimizations resulted in higher probabilities to select a band at very low frequencies (up to 2 Hz) and at frequencies between 3 and 8 Hz, but scarcely at higher frequencies. The outcome of all calculations was summed and normalized (Figure 5) and is an estimate of how relevant are single frequencies to perform an optimal microsleep detection. This way, GA-OLVQ1 provides a way to extract knowledge from subsymbolic machine learning.

CONCLUSIONS

We have presented five different cases of feature reduction for the analysis of Microsleep events. Best results, with test errors down to 10 %, were obtained by dynamic adaptation of spectral bands for each signal utilizing genetic algorithms. Such an adaptation of frequency bands enables three facts. First, it reduces the number of features as well as the complexity of the problem which resulted in increased detection performance. Second, it lowers computational costs, and third, this methodology extracts knowledge on relevance or irrelevance of single PSD values in order to detect microsleep events.

Results showed common averaging of PSD in four bands (delta, theta, alpha, beta) to be outperformed by averaging in many spectral bands. SVM are less sensitive to high number of input features than OLVQ1. In the future OLVQ1 should be replaced by SVM in order to estimate training set errors. In the presented framework these estimates serve as fitness function of a genetic algorithm. In parallel, multiple hold-out validation should be replaced by leave-one-out validation which is an almost unbiased estimator of the true classification error. Furthermore, it should be considered to set the number of frequency bands per signal completely free. But, the basis for all future improvements is the expected rapid increase of computational power.

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