Predictive modeling of human operator cognitive state via sparse and robust support vector machines

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Received: 27 August 2012 / Revised: 11 December 2012 / Accepted: 10 January 2013 / Published online: 20 January 2013
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Abstract The accurate prediction of the temporal variations in human operator cognitive state (HCS) is of great practical importance in many real-world safety-critical situations. However, since the relationship between the HCS and electrophysiological responses of the operator is basically unknown, complicated and uncertain, only data-based modeling method can be employed. This paper is aimed at constructing a data-driven computationally intelligent model, based on multiple psychophysiological and performance measures, to accurately estimate the HCS in the context of a safety-critical human–machine system. The advanced least squares support vector machines (LS-SVM), whose parameters are optimized by grid search and cross-validation techniques, are adopted for the purpose of predictive modeling of the HCS. The sparse and weighted LS-SVM (WLS-SVM) were proposed by Suykens et al. to overcome the deficiency of the standard LS-SVM in lacking sparseness and robustness. This paper adopted those two improved LS-SVM algorithms to model the HCS based

solely on a set of physiological and operator performance data. The results showed that the sparse LS-SVM can obtain HCS models with sparseness with almost no loss of modeling accuracy, while the WLS-SVM leads to models which are robust in case of noisy training data. Both intelligent system modeling approaches are shown to be capable of capturing the temporal fluctuation trends of the HCS because of their superior generalization performance.

Keywords Human operator cognitive state · Least squares support vector machine · Sparseness · Robustness · Regressive model

Introduction

In the operation of complex systems in public transport (for example aviation and space) industry, the human operator would inevitably become fatigued, overloaded or excessively stressful. The accidents caused by the detriment (or impairment) of Human operator cognitive state (HCS) occurred now and then. Therefore, an important factor for the evaluation of an ergonomic design in engineering is whether or not the accidents can be avoided or at least reduced as much as possible. The need for operator functional state (OFS) assessment is prompted by a growing worldwide concern with the consequences of performance breakdown of operators in safety-critical task environments.

OFS definition

OFS is defined as the multidimensional pattern of human psychophysiological condition that mediates performance in relation to physiological and psychological costs (Wilson 2001, 2002a, b, c; Wilson and Schlegel 2004;

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Wilson et al. 2000). OFS results from the synthesis of operator characteristics, current operator condition, and the operator's interaction with operational requirements. In other words, OFS can be regarded as the result of many physiological and psychological processes that regulate brain and body in an attempt to maintain an individual operator in an optimal condition to meet the work demands (Gaillard and Kramer 2000).

Despite increasing use of various automation technologies, the human operator has an increasingly central role in the execution of tasks. In addition, both work related and unrelated *risk factors* impose increased demands (such as stress, time pressure, etc.) and present a cumulative challenge to stress adaptation mechanisms. Such issues have been generally appreciated in the human factors community. There have been a number of surveys on the widely-used methods for assessing workload, fatigue, and the impact of stress and task demands on performance and situation awareness since 1980s (Backs and Boucsein 2000; Hancock and Desmond 2001). However, in practice the accurate prediction of performance breakdown has been hindered by the inadequacy of methods for taking account of the so-called compensatory behavior of human operators. It has been recognized that effective performance requires the operator to achieve a trade-off between the benefits of sustaining primary task goals and the costs of depleting limited energetical resources (Hockey 1997; Hockey et al. 2009). The need to preserve resources is essential if operators are to respond effectively to unexpected demands or emergency situations, such as an unanticipated navigational hazard or failure of an automatic control system.

It is often impossible to determine whether or not an operator is capable of carrying out a task by simply measuring overt performance because of the strategic reallocation of mental capacity. However, intelligent data analysis may reveal 'latent decrements' in the form of increased effort and strain, errors in secondary tasks, or increased activation and disturbances in the underlying physiological systems. The same kind of compensatory mechanisms have been found in the response to stress and difficult task conditions, such as cognitive load and shift work. Skilled, highly-motivated operators in real-world safety-critical tasks normally maintain overt performance very effectively, even under severe demand and stress. Where breakdown does occur, it is often characterized by a graceful degradation' rather than catastrophic failure. For a period before manifest performance degradation can be observed, the operator is likely to be in a risky or vulnerable functional state, being able only to manage predictable, routine task demands or produce bursts of high-effort control. By monitoring the occurrence of such states, serious consequences of performance breakdown can be prevented.

OFS assessment framework

OFS assessment should enable the prediction of an individual operator's performance at a particular time instant. The assessment is likely based on a psychophysiological model. The goal of this work is to present a data-based intelligent OFS assessment method based on support vector machines (SVMs). Figure 1 shows an OFS assessment framework, in which important concepts are included. The most important reason to assess the operator state is to prevent a performance breakdown. However, there is no direct relation between state and performance. The operator has to *process relevant information* (tasks) in order achieve an adequate level of *performance*. An operator can only do so when his or her state fits the required state for that particular task, otherwise the level of performance will not be optimal.

An important mechanism for regulating large discrepancies is mental effort. When operators are required to sustain performance on cognitively demanding tasks, they can only do so by increasing mental effort. This compensatory mechanism preserves performance levels at the expense of incurring additional costs. If this state regulation process does not have the required result, the operator can sometimes manage excessive task demand by changing the *strategy*. For example, he or she may decide to concentrate on the primary tasks only and not to pay attention to secondary tasks or to reduce the reliance on immediate memory and make more use of external memory aids, such as charts and tables.

Because of the "protective" (compensatory) effect of increased effort, it is obvious that performance measures alone are insufficient to assess the operator state. The performance level does not provide information about the costs involved in the adaptive response to mental stress. Particularly under conditions of performance protection

Fig. 1 An OFS assessment conceptual framework

(where there is no discernible breakdown under stress), physiological and subjective measures of OFS during task performance mainly reflect the amount of mental effort (strain) required to maintain task performance (Hoyt 2010). A major challenge is to assess the operator state and to predict breakdowns in performance in real-time. One way to meet this challenge is through use of adaptive automation (Scerbo et al. 2000, 2001; Wang et al. 2012). Once the unstable, vulnerable or risky state is detected, demands on the operator can be dynamically reduced by allocating more tasks to a machine (or computer).

Application of OFS assessment and monitoring: adaptive automation (AA) strategy

In traditional control and automation field, the researchers have realized that the idea of complete removal of human supervision or intervention would be impractical. In an attempt to furnish more personalized and intelligent automation system solutions, the old idea of full automation has had to change and the essential theoretical issue concerns about the degree of autonomy fittest to human–machine cooperative control or automation systems (Bainbridge 1983). Fitts (1951) first proposed a method of functional allocation between human and machine for automated system design.

The human-centered automation (HCA) systems may have better performance than those based on the idea of making them automated (automatic) as much as possible. When the environmental conditions change, the systems would be unable to maintain the strengths of the HCA design methodologies. The automation solutions must be sufficiently intelligent such that the level of automation (LOA) can adapt to the changes in the environmental conditions, which is referred to as adaptive automation or adjustable autonomy (AA) (Parasuraman et al. 2000; Bradshaw et al. 2002).

The AA is defined as the technology that can change its mode of operation dynamically. Furthermore, both the technology and operator can initiate changes in the level (degree), mode or type of automation (or autonomy, so-called AA) (Parasuraman 2000). Historically, the development of AA was originated from the artificial intelligence (AI) research in the 1970s with an aim of developing adaptive aiding to help allocate tasks between humans and computers (Rouse 1976, 1977). A significant development was the use of intelligent systems to assist pilots of advanced (high performance) fighter aircraft by supplying them with information in the appropriate format when needed. This program, called the Pilot's Associate, was a joint effort among DARPA, Lockheed, McDonnell, and Wright R&D Center. The system was a network of cooperative knowledge-based subsystems that could

monitor and assess events and then formulate plans to respond to problems (Hammer and Small 1995). On the other hand, the U.S. army program on Rotorcraft Pilot's Associate (RPA), an intelligent “crew member” for the next-generation attack helicopters, was also carried out (Colucci 1995).

Motivations, aims and objectives of present work

From ergonomic (or human factors) perspective, the occurrence of the accidents is often due to the fact that the instantaneous demands on the operator from the system and environment exceed the operator capacity of load-handling. An effective way of addressing the problem is to adjust the control strategy of the human–machine systems based on the HCS analysis (or assessment) (Hockey 2003). By means of the HCS recognition, an adaptive aiding system can be designed either to give out warnings to the operator or to reduce the task demand during the period of excessively high mental workload (MWL) (Kuriyagawa and Kageyama 1999), so as to realize an optimal task allocation between the human operator and technical systems to make them work together safely and efficiently.

The psychophysiological measures reflect the information regarding various physiological and mental status of human being (Prinzel et al. 2000; Gao et al. 2011; Lee et al. 2012; Werner 2012; Zhang and Lee 2012). The continuously measurable psychophysiological signals can provide with us the real-time information in relation to the HCS, among which the electroencephalogram (EEG) signals are the collective response of a large number of neurons in the brain measured on the scalp and thus the study on the EEG signals has become an effective way to better understand the brain functions and the interrelationship between thought and behaviors (Gevins et al. 1998; Trejo et al. 2003; Pockett et al. 2007; Chen et al. 2008). The characteristics of the electrocardiogram (ECG) signal respond well to the load or stress conditions, e.g., the ECG, blood pressure, and respiration rate were shown to be considerably different when the operator is in a strained or fatigue state from those in a normal resting state (Wilson and Fisher 1991; Greene et al. 2000). Some studies have shown that in the environment of higher-level problem-solving, the commonly-used cardiovascular indices, such as heart rate (HR) and heart rate variability (HRV), reliably respond to the variations in the HCS (Jorna 1993).

There has been some work which used electrophysiological signals to assess the HCS (Gevins and Smith 1999; Wilson and Fisher 1995; Russell and Wilson 1998; Wilson and Eggemeier 1991). The existing results have shown that different physiological signals can reflect particular aspects of the HCS, for instance the HR can be used to determine the overall attention of the operator to the tasks,

while the EEG signals are quite sensitive to the change of cognitive and behavioral state. Most previous studies on the HCS used EEG data, which initially demonstrated the feasibility of using physiological data for the HCS evaluation.

The SVM is a powerful machine learning method based on the statistical learning theory proposed by Vapnik (1995). The generalization capacity of the learning machine is enhanced by the structural risk minimization (SRM) so as to obtain satisfactory statistical laws even in the presence of small sample. Nevertheless, the standard SVM requires a solution of the convex quadratic programming problem with heavy computational overload. As a special form of the standard SVM in the case of quadratic loss function, the least squares SVM (LS-SVM) was then proposed by Suykens and Vandewalle (1999) to replace the solution of convex quadratic programming problem by that of a system of equations, which reduces the computational complexity and improves both the efficiency and precision of the solution. Hence, the LS-SVM method received a wide range of applications to functional approximation and estimation problems. Nevertheless, there are two serious drawbacks of the LS-SVM method, including (1) all training samples are support vectors, which leads to the loss of solution sparseness. As a result, not only a large memory is required to save those support vectors, but also the generalization capability of the model is affected, (2) All training samples are equally penalized in the objective function and thus the robustness of the estimation would be bad if the given samples are noisy.

Suykens et al. developed a simple pruning algorithm (Suykens et al. 2000) to overcome the sparseness problem related to the LS-SVM method and a weighted version of least squares support vector machine (WLS-SVM) (Suykens et al. 2002) to address the robustness problem. In this work the measured ECG, EEG and human performance data was used for the HCS assessment. Based on a fusion of the physiological and performance data, a HCS model with both sparseness and robustness properties was constructed by employing the two enhanced versions of the LS-SVM method proposed by Suykens et al. (2000, 2002).

Experiments

Data acquisition

The automation-enhanced Cabin Air Management System (aCAMS) is adopted in this work to simulate a safety-critical and highly complex multi-task process control environment. It was originally developed for the European Space Agency (ESA) and used for investigating various stressors of the astronauts working and living under highly

separated and confined environment (Hockey et al. 1998). In this system, the human operator is required: (1) to maintain the five key controlled variables, including CO₂, oxygen, air pressure, temperature and humidity in the closed cabin within their respective ranges of target, and (2) to cope with the programmed faults or failures promptly, for instance the operator may be required to perform manual controls to guarantee the normal operation of the system so long as the faults or failures continue or some automatic controllers malfunctions.

A total of 10 subjects, who are all college students with engineering major and are coded as A, C, D, E, F, G, H, J, K, and L, respectively, participated in the experiments. In order make them familiarized with the aCAMS as well as the simulated control tasks, before the formal sessions of the experiment all subjects underwent a training lasting more than 10 h. The experiment on each subject consisted of 2 sessions, which were arranged at the same time period of different days in order to avoid the effect of circadian rhythms. Each session comprises 9 task-load conditions with each condition lasting for 15 min and hence the whole session of experiment lasted for $15 \times 9 = 135$ min. To simulate the different levels of task load, under the 9 task-load conditions, the number of controlled variables demanding manual control by the subject was varied across conditions in such a stepwise and cyclical scheme as $1 \rightarrow 2 \rightarrow 3 \rightarrow 4 \rightarrow 5 \rightarrow 4 \rightarrow 3 \rightarrow 2 \rightarrow 1$. At the start of each task-load condition, the subject was asked to provide some subjective ratings of their status such as efforts, fatigue and anxiety. During the period of the whole session the EEG and HR data was recorded. The multi-channel EEG data was sampled at 2048 Hz according to the international 10–20 electrode placement system, while the HR data recorded at a rate of 1 Hz. Furthermore, all the five key controlled variables were measured in real time to derive the index of the primary-task performance of the human operator.

Data preprocessing

The physiological markers of HR, HRV₂, TLI₁, TLI₂ have shown to be relatively sensitive to the change of the MWL (Nickel et al. 2005; Zhang et al. 2006). The HR index is taken as the average value of the HR time-series data within a minute. HRV₂ is defined as the ratio between the standard deviation and mean value of the HR time-series data within a minute (Zhang et al. 2008) and given by:

$$HRV_2 = \frac{\sigma_{HRV}}{\mu_{HRV}} \quad (1)$$

The EEG-based task load indices (TLI) are defined as the ratio of EEG band powers measured from different channels, i.e.,

$$TLI_1 = \frac{P_{\theta, Fz}}{P_{\alpha, Pz}} \quad (2)$$

$$TLI_2 = \frac{P_{\theta, AFz}}{P_{\alpha, CPzPOz}} \quad (3)$$

where P_{θ} and P_{α} stand for the EEG power in θ and α frequency subbands, respectively, with finer division of the frequency subbands at 5 different electrode locations (i.e., Fz, Pz, AFz, CPz and POz in international 10–20 electrode placement system) as—(Fz, θ):6–7 Hz; (AFz, θ):5–7 Hz, (Pz, α):10.5–12.5 Hz; (CPz, α):8–10 Hz; (POz, α):10.5–12.5 Hz.

The NOV (Number of Variables to be manually controlled), indicative of the level of the task difficulty, is defined by:

$$NOV = \begin{cases} 1, & \text{for C1 and C9} \\ 2, & \text{for C2 and C8} \\ 3, & \text{for C3 and C7} \\ 4, & \text{for C4 and C6} \\ 5, & \text{for C5} \end{cases} \quad (4)$$

where C1–C9 represents the 9 consecutive task-load conditions, respectively, in the experimental session. From the primary task performance data, we derived an index called *TIR* (Time-In-Range) to evaluate the operator task performance. The *TIR* is defined as the percentage of the time instants in a minute, at which all five controlled variables are within the target ranges.

Methods

Standard LS-SVM algorithm

Given the training data-set $D = \{(\mathbf{x}_i, y_i) | i = 1, 2, \dots, l\}$, $\mathbf{x}_i \in R^n$, $y_i \in R$. According to the SRM principle by Vapnik (1995) and taking into consideration both the functional complexity and fitting error, the regression problem can be formulated as the following constrained optimization:

$$\begin{cases} \min & \frac{1}{2} \|\mathbf{w}\|^2 + \frac{1}{2} C \sum_{i=1}^l \xi_i^2 \\ \text{s.t.} & y_i = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_i) + b + \xi_i, \quad i = 1, 2, \dots, l. \end{cases} \quad (5)$$

where $\mathbf{w}$ is the weight vector in the space R^n , which is orthogonal with the hyper-plane $\mathbf{w}^T \mathbf{x} + b = 0$, C the penalty factor, ξ_i the relaxation variable, b the bias, and $\boldsymbol{\varphi}(\mathbf{x}_i)$ maps the input space onto the higher-dimensional feature space.

Based on the objective function and constraints, the Lagrangian function is constructed as:

$$L = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} C \sum_{i=1}^l \xi_i^2 - \sum_{i=1}^l \alpha_i [\mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_i) + b + \xi_i - y_i] \quad (6)$$

where $\alpha_i (i = 1, 2, \dots, l)$ is called the Lagrangian multipliers.

Define the kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \boldsymbol{\varphi}(\mathbf{x}_i)^T \boldsymbol{\varphi}(\mathbf{x}_j)$ as the symmetrical function satisfying the Mercer condition, then the optimization problem can be transformed into solving simultaneous linear equations, finally we obtain the regression function:

$$f(\mathbf{x}) = \sum_{i=1}^l \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b. \quad (7)$$

The choice of different kernel functions would lead to different SVMs, among which the RBF (radial-basis function) kernels have been most widely used due to their wide range of applicability. Hence, the RBF kernel in the following form was also adopted in this work:

$$K(\mathbf{x}_i, \mathbf{x}) = \exp(-\|\mathbf{x} - \mathbf{x}_i\|^2 / \sigma^2) \quad (8)$$

where σ^2 is an adjustable constant.

Sparse LS-SVM (SLS-SVM) algorithm

The fundamental idea of the pruning algorithm (Suykens et al. 2000) is as follows: after training with the training dataset, arrange $|\alpha_i|$, $i = 1, 2, \dots, l$ in the descent order of the values. Remove those samples corresponding to smaller $|\alpha_i|$ to constitute a smaller subset of training data. With this subset of training data, a new LS-SVM can be generated. In the similar way, the training samples corresponding to smaller $|\alpha_i|$ in the original training dataset can be progressively removed and new SVMs are thus constructed until the training precision of the latest sparse LS-SVM exceeds an allowable value. Since the most important samples are contained in the subset of the training data, the new LS-SVM obtained is supposed to possess the generalization performance comparable to that of the original LS-SVM. On the other hand, due to the reduction in the number of training samples, the number of support vectors of the newly obtained LS-SVM is considerably less than that of the original LS-SVM, in other words, the new LS-SVM has better sparseness property than the original one. This algorithm was first proposed to obtain the sparse LS-SVM classifier and later extended to solve the function estimation problems.

Weighted LS-SVM (WLS-SVM) algorithm

The WLS-SVM is the result of re-training the LS-SVM (Suykens et al. 2002). First, the initial training is performed using the training samples. After obtaining the Lagrangian multipliers α_i , the different weight v_i can be placed on the error variable $\xi_i = \alpha_i / C$. In this way, the retrained LS-SVM would possess better robustness property. The WLS-SVM based regression problem can be formulated as the following optimization:

$$\begin{cases} \min & \frac{1}{2} \mathbf{w}^T \mathbf{w} + \frac{1}{2} C \sum_{i=1}^l v_i \xi_i^2 \\ \text{s.t.} & y_i = \mathbf{w}^T \boldsymbol{\varphi}(\mathbf{x}_i) + b + \xi_i, \quad i = 1, 2, \dots, l \end{cases} \quad (9)$$

where the weight v_i is selected according to the error variable $\xi_i = \alpha_i/C$ in un-weighted LS-SVM and used to optimize the value of α_i . The concrete value of v_i is commonly determined by the formula (Suykens et al. 2002):

$$v_i = \begin{cases} 1, & \text{if } |\xi_i/\hat{s}| \leq c_1 \\ \frac{c_2 - |\xi_i/\hat{s}|}{c_2 - c_1}, & \text{if } c_1 < |\xi_i/\hat{s}| \leq c_2 \\ 10^{-4}, & \text{otherwise} \end{cases} \quad (10)$$

where c_1 and c_2 are constants, whose typical values are taken as $c_1 = 2.5$ and $c_2 = 3$, and $\hat{s}$ is a robust estimate of the standard deviation of the error variable ξ_i of the LS-SVM and measures the degree of deviation of ξ_i from Gaussian distribution. $\hat{s}$ can be calculated by (Rousseeuw and Leroy 1987; Hampel et al. 1986):

$$\hat{s} = 1.483 \text{MAD}(\xi_i) \quad (11)$$

where $\text{MAD}(\xi_i)$ denotes the mean absolute deviation (MAD) of the error variable ξ_i and is defined by:

$$\text{MAD}(\xi_i) = \frac{1}{l} \sum_{i=1}^l \left| \xi_i - \frac{1}{l} \sum_{i=1}^l \xi_i \right|. \quad (12)$$

Table 1 The model inputs selected for each of the 10 subjects

Subject	A	C	D	E	F	G	H	J	K	L
Input variable										
HR				✓				✓		
HRV ₂		✓	✓			✓				✓
TLI ₁	✓	✓		✓			✓	✓		✓
TLI ₂	✓	✓		✓	✓	✓			✓	
NOV	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Determination of HCS model structure

The five candidate input variables of the HCS model include *HR*, *HRV₂*, *TLI₁*, *TLI₂*, and *NOV*, while the model output is *TIR*. The optimal model inputs for each subject were selected according to the relative sensitivity of the five candidate inputs to the LS-SVM modeling accuracy, which were shown in Table 1 (the symbol “✓” stands for the selected input).

All the data were re-sampled with an interval of 1 min. Due to the period of filling in the subjective ratings and questionnaire, the first and last 30 s. data in each task-load condition were removed. Finally we have 2 dataset from 2 sessions, each lasting for 126 min, for each subject. The dataset of first session (s1 in short hereafter) was used as the training data, while the testing data uses the 2nd session (s2 in short hereafter) data. The I/O training (left panel) and

Fig. 2 The I/O data (left training data-set; right testing dataset) **a** subject H; **b** subject K

Table 2 The model parameters for each of the 10 subjects

Subject		A	C	D	E	F	G	H	J	K	L
Model parameters	C	25.4305	85.2563	26.878	14.3514	1335.9072	4.5834	520.4908	41.0663	203.0544	76.3975
	σ^2	298.824	97.9189	34.2191	32.6788	1.1469	26.9066	84.5972	17.7788	17.5023	102.9191

testing (right panel) data for subject H and K were shown in Fig. 2a, b, respectively. The parameters C and σ^2 were optimized by using the grid search and 10-fold cross-validation techniques. Their optimal values are given in Table 2.

HCS Modeling based on SLS-SVM and WLS-SVM Algorithms

All the algorithms were implemented by programming with MATLAB 7.1, which was run under Windows XP with the CPU clock frequency of 1.8 GHz and a 1G memory. In the following, the specific procedures for the sparse LS-SVM and WLS-SVM based HCS modeling are presented. Incorporating Suykens's pruning algorithm (Suykens et al. 2000), the procedure of the sparse LS-SVM algorithm adopted is composed of the following steps:

Step 1 For the given 126 training samples, let $l_t = l = 126$ and $t = 1$.

Step 2 Based on the 126 training samples, the initial LS-SVM training was carried out. Use the initial training

dataset as the testing data with the model performance index as the following Mean Absolute Error:

$$MAE_t = \frac{1}{l_t} \sum_{i=1}^{l_t} |y(i) - y_M(i)| \quad (13)$$

where $y(i)$ and $y_M(i)$ are the actual (or desired) and model output, respectively.

Step 3 Arrange $|x_i|$, $i = 1, 2, \dots, l_t$, which are obtained in Step2, in descent order of the values and then remove those samples corresponding to smaller $|x_i|$. In general the model generalization accuracy would be unacceptable due to inadequate training if too many samples are removed, therefore, the maximum number of the removed samples is set to be 5 % of the total number of the training samples.

Step 4 Set $t \leftarrow t + 1$, let the number of the removed samples to be k , then the number of remaining samples is $l_t = l_{t-1} - k$. Keep the remaining samples to form a subset of training data.

Step 5 Retrain the LS-SVM using the new training dataset and use the initial dataset as the testing data to calculate the predictive error MAE_t of the model.

Fig. 3 The output surface of the sparse LS-SVM model **a** subject H; **b** subject K

Fig. 4 The output surface of the WLS-SVM model **a** subject H; **b** subject K

Fig. 5 Comparison of LS-SVM model output and training data and testing data **a** subject H; **b** subject K

Step 6 Loop back to Step3 until the algorithm stops when $MAE_t * 95\% > MAE_1$.

The resulting LS-SVM regressive model is $f(x) = \sum_{i=1}^l \alpha_i K(x_i, x) + b$.

The concrete modeling procedure of WLS-SVM is given as follows:

Step 1 For the given 126 training samples, solve the simultaneous linear equations of the unweighted LS-SVM to obtain α_i , $i = 1, 2, \dots, 126$ and b .

Step 2 Calculate the error variable $\xi_i = \alpha_i / C$.

Step 3 Compute $\hat{s}$, according to Eq. (11), from the distribution of ξ_i .

Fig. 6 Comparison of WLS-SVM model output and training data and testing data **a** subject H; **b** subject K

Step 4 Determine the weights v_i from ξ_i and $\hat{s}$ according to Eq. (10).

Step 5 Solve the simultaneous linear equations of the WLS-SVM to obtain new α_i^* , $i = 1, 2, \dots, 126$ and b^* . Hence the WLS-SVM regressive model is thus obtained as $f(x) = \sum_{i=1}^l \alpha_i^* K(x_i, x) + b^*$.

If both robustness and sparseness properties are desired for the LS-SVM, the robust training can be first performed based on the initial training, then the sparse training proceeds. Eventually we have the model of the weighted sparse LS-SVM (WSLS-SVM).

Modeling results and analysis

The model evaluation is performed by calculating the residual error E , MAE and training and testing time required. The sparse LS-SVM model output surface for subject H and K is shown in Fig. 3a, b, respectively, while the WLS-SVM model surface for two subjects is shown in Fig. 4a, b, respectively. The comparison of the LS-SVM model output and desired output for subject H and K is shown in Fig. 5a, b, respectively and the comparison of the WLS-SVM model

output and desired output for them is shown in Fig. 6a, b, respectively. The comparison of modeling error between LS-SVM and WLS-SVM models for subject H and K is shown in Fig. 7a, b, respectively. The WLS-SVM model output surface for subject H and K is shown in Fig. 8a, b, respectively. From Figs. 5, 6 and 7, it is recognized that the WLS-SVM models have a better fit with the training and testing data with smaller modeling residual error, which indicated that the models are somehow insensitive to the noisy training data. Nevertheless, due to the complex and nonstationary dynamics of the training data and also its limited number, the data-based models are somewhat insufficient to completely characterize the global variations of the HCS, which may explain the modeling error outliers appearing at certain time instants.

The comparison of training and testing errors and time required between the standard LS-SVM and sparse LS-SVM is given in Table 3, in which the symbol N_{sv} stands for the number of support vectors and N the number of pruning iteration. It is seen that for most subjects except for G, the testing errors of the sparse LS-SVM models become only slightly larger than those of the standard LS-SVM models, which indicates that the sparse LS-SVM models are sufficiently accurate for the purpose of HCS modeling. On the

Fig. 7 Comparison of training and testing errors between LS-SVM and WLS-SVM models **a** subject H; **b** subject K

Fig. 8 The output surface of the WLS-SVM model **a** subject H; **b** subject K

Table 3 Comparison of the training and test errors and time between LS-SVM and sparse LS-SVM models for each of the 10 subjects

Subject	LS-SVM ($N_{sv} = 126, N = 0$)				Sparse LS-SVM					
	Training		Test		N_{sv}	N	Training		Test	
	MAE	Time (ms)	MAE	Time (ms)			MAE	Time (ms)	MAE	Time (ms)
A	9.163	19.04	7.9268	5.64	50	3	9.7873	472.8	7.9688	3.42
C	10.8205	39.04	11.282	5.81	54	11	11.944	683.42	12.9998	3.54
D	8.5902	23.73	8.7259	5.94	96	33	9.3358	240.71	9.8472	5.01
E	12.8161	38.84	10.5024	6.37	93	7	13.5865	365.37	11.877	5.32
F	2.9039	168.33	7.3994	6.43	100	24	3.0675	1052.89	7.9251	5.59
G	21.1768	26.98	22.8612	5.86	48	29	22.3614	607.05	22.4384	3.61
H	7.6567	26.71	8.8318	5.21	108	21	8.1333	177.89	9.1705	4.8
J	13.4388	50.97	17.9385	6.36	104	9	14.4262	346.58	18.4141	5.59
K	5.0451	44.1	5.5289	5.62	100	7	5.4553	342.01	5.7541	4.8
L	15.5055	29.02	11.8129	5.58	93	12	16.679	295.85	13.8833	4.9

Table 4 Comparison of training and testing error between standard LS-SVM and WLS-SVM models for each of the 10 subjects

Subject	LS-SVM		WLS-SVM	
	MAE (train)	MAE (test)	MAE (train)	MAE (test)
A	9.163	7.9268	8.2617	6.4283
C	10.8205	11.282	10.1048	11.0406
D	8.5902	8.7259	7.7277	7.8487
E	12.8161	10.5024	12.5765	10.6285
F	2.9039	7.3994	2.7867	7.5632
G	21.1768	22.8612	21.1008	22.2447
H	7.6567	8.8318	6.8885	7.4669
J	13.4388	17.9385	13.2751	16.8035
K	5.0451	5.5289	4.1911	4.8629
L	15.5055	11.8129	14.4087	11.1463

Table 5 Comparison of training and testing error between sparse LS-SVM and WLS-SVM models for each of the 10 subjects

Subject	Sparse LS-SVM			WLS-SVM		
	N_{sv}	MAE (train)	MAE (test)	N_{sv}	MAE (train)	MAE (test)
A	50	9.7873	7.9688	116	8.2877	6.44
C	54	11.944	12.9998	87	10.41	11.0623
D	96	9.3358	9.8472	40	8.612	8.537
E	93	13.5865	11.877	100	13.1752	12.2168
F	100	3.0675	7.9251	58	3.7299	8.0502
G	48	22.3614	22.4384	48	22.7712	18.9776
H	108	8.1333	9.1705	64	7.5219	8.3395
J	104	14.4262	18.4141	93	14.4242	18.8573
K	100	5.4553	5.7541	100	4.4742	5.0007
L	93	16.6796	13.8833	84	15.1915	11.869

other hand, after pruning N_{sv} was significantly reduced. For instance, for subject A and G, before pruning N_{sv} is all the same for all subjects, i.e., $N_{sv} = 126$ (in this case, all samples were used as the support vectors by the SVM), while it is reduced to 50 and 48, respectively after pruning. In comparison, the computational time required for testing the sparse LS-SVM models are less than that of the standard LS-SVM models due to the use of sparse support vectors, for instance for subject A and G the model testing time required is reduced from 5.64 and 5.86 ms to 3.42 and 3.61 ms, respectively. It is also observed from Table 3 that the smaller the N_{sv} , the more significant the reduction in model testing time. Nonetheless, the computational time required by training the sparse LS-SVM models becomes longer than that of the standard LS-SVM models. In order to obtain the sparse solution of the LS-SVM, the original LS-SVM has to be solved first and then the pruning algorithm of iterative nature must be carried out. For each iterative epoch, a re-training of the model, involving a solution of KKT linear systems, has to be performed. For example, for subject H and K, 21 and 7 pruning was carried out, respectively. This explained why the training time was prolonged for sparse LS-SVM models, as shown in Table 3.

Table 4 compared the training and testing errors between the LS-SVM and WLS-SVM, while that between the sparse LS-SVM and WLS-SVM is given in Table 5. From Table 4, it is seen that the training error of the WLS-SVM models for all ten subjects is reduced and the testing error is also reduced for most subjects except for subject E and F. For instance, for subject H the training and testing errors were reduced from 7.6567 and 8.8318 to 6.8885 and 7.4669, respectively, while for subject K they were reduced from 5.0451 and 5.5289 to 4.1911 and 4.8629, respectively. The comparative results suggest that

the WLS-SVM models have higher accuracy and robustness with regard to the noise mixed in the training data. From Table 5, it is noted that for most subjects (except for A, C and E) N_{sv} of the WSLS-SVM models is unchanged or smaller than that of the sparse LS-SVM models, indicating that the computational complexity of both types of model is similar. On the other hand, the training and testing errors of the WSLS-SVM models are reduced for most subjects except for E and F. Therefore, in comparison with the sparse LS-SVM models, the WLS-SVM models, which improved both the robustness and sparseness of the LS-SVM models (Qin and Zhang 2012), generally have better HCS prediction performance of our interest.

Summary and conclusions

The human operator's ability to perform required tasks or missions can fluctuate over time. Because the cognitive demands of the work can also vary, it is possible that the capabilities of the operator are insufficient for the work demands. This can lead to errors when the operator is overwhelmed by the task demands. Psychophysiological measures, such as HR and brain activities, can be used to monitor operator's cognitive workload. In this work a few most salient psychophysiological features have been selected to quantitatively evaluate OFS based on SVMs. The results have demonstrated that the pruning-based SVM algorithm simplifies the HCS model structure of the LS-SVM, developed in Qin and Zhang (2012), by using only sparse support vectors but ensures the sufficient regression performance. However, the reduced testing time of the pruning SVM algorithm is achieved at the expense of prolonged model training time and slight loss of accuracy. The WLS-SVM was also shown to be capable of enhancing the robustness of standard SVM. Overall, the WSLS-SVM method equips the LS-SVM model training with both sparseness and robustness properties, leading to computationally-efficient HCS models with reasonably accurate generalization (or prediction) performance. To summarize and in conclusion, by a series of laboratory-based experimental data analysis results on different subjects we show that the data-driven modeling method proposed is able to accurately model the large noisy and nonlinear psychophysiological dataset. The proposed OFS predictive modeling methods have potential to be used as a solid basis for further designing and implementing adaptive human-machine systems with enhanced performance and safety in the safety-critical situations.

Acknowledgments The authors would also like to thank Prof. D Manzey, Technical University Berlin, Germany, for providing the AUTO-CAMS software used in our OFS data acquisition experiments. The work supported by the National Natural Science Foundation of

China (under Grant No. 61075070 and Key Grant No. 11232005) and a Senior Research Fellowship from the Max Planck Institute for Dynamics of Complex Technical Systems, Magdeburg, Germany.

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