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IFAC-PapersOnLine 49-19 (2016) 561–566

# Mental Workload Recognition by Combining Wavelet Packet Transform and Kernel Spectral Regression Techniques

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**Abstract:** A Mental Workload (MWL) recognition system was developed based on psychophysiological data to assess temporal variations in MWL levels. Salient EEG features were first extracted by using fuzzy mutual-information- based wavelet-packet transform (FMI-WPT). Then we adopted the kernel spectral regression linear discriminant analysis (KSRDA) to reduce the EEG feature dimensionality and to simultaneously enhance the inter-class discrimination capacity of the MWL classifiers. By combining FMI-WPT and KSRDA techniques, we designed, evaluated and compared different types of MWL classifiers. The results demonstrated a improvement of the MWL classification accuracy by the proposed feature reduction method and classifier design framework. Particularly, it was shown by extensive comparative studies that the KNN and SVM outperform other classifiers.



*Keywords:* mental workload, fuzzy mutual-information based wavelet packet transform, Kernel spectral regression discriminant analysis, physiological signals

## 1. INTRODUCTION

In modern complex systems, the operator is demanded to continually adapt to new and unforeseen changes in the dynamic process under control. This includes making decision on whether and what actions are required to do in human-machine collaboration systems (HM systems). Despite the widespread benefits of automation, there are also some well-known problems for operator effectiveness. In order to reduce operator performance degradation caused by both factors above, researchers have begun to turn attention to the research of how to keep the optimal operator functional state (OFS) of HM systems.

According to the recent studies, MWL indirectly reflects the OFS of the operator and accurate estimations of MWL are crucial in OFS assessment. Many techniques have been developed on OFS assessment including methods identifying physiological associations between MWL and the corresponding patterns of the electroencephalogram (EEG), electroocculogram (EOG), and electrocardiogram (ECG) signals. Our reported works have paid much attention to improving the OFS assessment results by improving the dimension reduction methods and the classifiers. However, what comes first of the recognition system of MWL is feature extraction procedure. Additionally, in his paper, the fuzzy mutual-information (FMI) based wavelet packet transform feature extraction method (FMI-WPT) was used for extracting features to classify the driver drowsiness state that similar to MWL and achieved impressive performance.

In this paper, the FMI-WPT feature extraction method was employed for extracting features to classify the MWL level into one of predefined levels. Furthermore, Kernel spectral regression linear discriminant analysis (KSRDA) technique was employed on the features to reduce the feature dimension and to highlight the inter-class discrimination. Then the different classifiers are applied to evaluate the MWL level.

The paper is organized as follows. The Section 2 will describe experimental in detail and the psychophysiological data preprocessing method. In Section 3, the FMI-WPT method will be described in detail, and in Section 4 the results of MWL classifications are shown. Section 5 shows the conclusions and future works.

## 2. DATA ACQUISITION EXPERIMENT: DESIGN AND PROCEDURE

### *2.1 Experimental environment*

The experiments were carried out on a simulated safety-critical human–machine system named Automation-enhanced Cabin Air Management System (ACAMS) with the sophisticated tasks. ACAMS simulates a life environment support system in the spacecraft. The ACAMS consists of four sub-systems simulating the corresponded four critical parameters in spacecraft.

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10.1016/j.ifacol.2016.10.626

Manual and automatic control mode were designed in each subsystem of ACAMS, which on behalf of that the task is controlled by the operator or the computer.

During the experiment, the number of subsystems (NOS) and the level of actuator sensitivity (LAS) are regarded as two complexity indicators. Thus, the manual control tasks with different NOS and LAS are supposed to represent different MWL level during the experiment.

### *2.2 Experimental Procedure*

Six participates in the experiment are postgraduates of East China University of Science and Technology to operate ACAMS. Additionally, the volunteers are male with the engineering background, healthy, right-handed (subjects A, B, C, D, E, F, 22–24 years, average age 23).

In ACAMS, each indicator varied relying on the related subsystem, and the subsystem is divided into two modes, manual control and automatic control, to control the NOS. Two levels of the actuator, standard level (SL) and high level (HL), were designed to control the difficulty of the task. SL and HL are the sensitivity level of the actuator. High level means that the variable change rate of the subsystems is very big. For the subject, more MWL will be need than the Standard level.

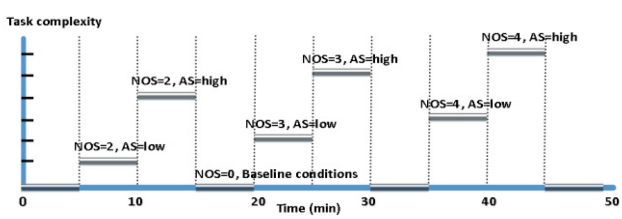


Fig. 1: Task load conditions in a session

To detect the changes of the MWL, two trails at the same time on different days were required to be performed on ACAMS. These twelve trials (6 subjects × 2 sessions) are denoted as A1, A2, B1, B2,..., F1, F2, respectively. Each session lasted 50 min and was divided into 10 conditions (i.e., each condition lasts 5 min, see Fig. 1). Additionally, the subject was ordered to give a self-assessment for his performance in the last 10 seconds of the condition, and signals of the last 10 seconds were omitted, data of 290 seconds was left for one condition. Finally, a dataset contained 17*1450000 (10*290*500) data was saved for each of the sessions, where 17 is the number of the channels, 290 is the time duration for 1 condition and there are 10 conditions in one session.

In conditions 1, 4, 7 and 10, automatically control mode was utilized to all the subsystems. In conditions 2 and 3, two of the subsystems (O2 and P) were defined as unactivated state, so the subject was required to control them manually with the actuator sensitivity in SL and HL, respectively. Similarly, three subsystems and four subsystems were unactivated state were shown in Fig.1. Specifically, to obtain accurate baseline signals and maintain the situation awareness of the task environment subject was also required to monitor the track of every subsystem, in conditions 1, 4, 7 and 10.

In the experiment, the psychophysiological data of the subjects were collected and recorded via EEG acquisition equipment. In this study, fifteen channels of EEG signals on the scalp based on 10-20 international electrode system were recorded with the sampling frequency of 500Hz and these channels are AFz, F3, F4, Fz, C3, C4, Cz, CPz, P3, P4, Pz, POz, O1, O2 and Oz. one channel ECG and one channel EOG were recorded. So, seventeen channels of signals were collected in the experiment. All signals have been filtered (0-40 Hz) by a Butterworth IIR filter. Then, the coherence method was used to remove the blink artifact in the frontal EEG before used in the study.

## 3. METHODS

The framework of the EEG-based MWL recognition system is illustrated in Fig 2.

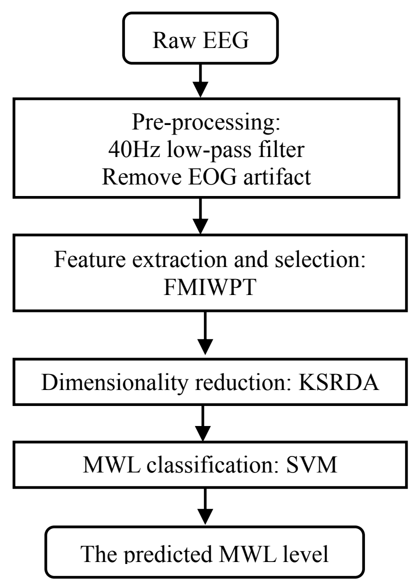


Fig. 2: EEG-based MWL recognition system.

The FMI-WPT algorithm is consisted of two parts: feature extraction in *Driver drowsiness classification using fuzzy wavelet-packet-based feature-extraction algorithm* and feature selection in Section 3.1.

### *3.1 EEG based feature selection in FMI-WPT*

In FMI-WPT, the feature selection procedure is to determine the best features set $X^*$ according to the maximum value of $F$. Here, $F$ is a measure weigh the importance of the specific feature.

Step 1: Sort the subspaces by $F$ in descending order, $\Omega = \{\Omega(1), \Omega(2), \cdots, \Omega(l)\}$.

Step 2: Move the first element in $\Omega$ to $X^*$.

Step 3: If $\forall \Omega(\mathrm{k}) \in \Omega$ , $\Omega(\mathrm{k})$ is an ascendant or descendant of $\Omega(\mathrm{j}_1)$, move $\Omega(\mathrm{k})$ from $\Omega$ to O.