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Task-generic mental fatigue recognition based on neurophysiological signals and dynamical deep extreme learning machine

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ABSTRACT

The electroencephalography (EEG) based machine-learning model for mental fatigue recognition can evaluate the reliability of the human operator performance. The task-generic model is particularly important since the time cost for preparing the task-specific training EEG dataset is avoid. This study develops a novel mental fatigue classifier, dynamical deep extreme learning machine (DD-ELM), to adapt the variation of the EEG feature distributions across two mental tasks. Different from the static deep learning approaches, DD-ELM iteratively updates the shallow weights at multiple time steps during the testing stage. The proposed method incorporates the both of the merits from the deep network for EEG feature abstraction and the ELM autoencoder for fast weight recompuation. The feasibility of the DD-ELM is validated by investigating EEG datasets recorded under two paradigms of AutoCAMS human–machine tasks. The accuracy comparison indicates the new classifier significantly outperforms several state-of-the-art mental fatigue estimators. By examining the CPU time, the computational burden of the DD-ELM is also acceptable for high-dimensional EEG features.

1. Introduction

In safety-critical working environments required human–machine collaboration, human operator is becoming a crucial factor that affects the task performance. To evaluate human–machine interaction efficiency, operator functional state (OFS) has been proposed to characterize human capability for prolonged monitoring and temporal strategy generation [1]. The abnormal OFS may cause instantaneous human performance degradation and increase the possibility of severe accidents in many public services such as driving, aviation, health care, and manufacturing [2]. According to well-documented studies [3–5], a group of variables, which are known as mental workload [6], situation awareness [7], and mental fatigue [8], quantify different aspects of OFS. In particular, mental fatigue is identified as a crucial dimension, which is defined by a cumulative process to the disinclination of the effort and drossiness.

Different from physical fatigue induced by the impaired muscular strength, mental fatigue is associated with the psychological responses indicated by the feelings of weariness and inhibition for continue performing the task [9]. Monotonous, long-hour working environments contribute to the gradual increase of the mental fatigue. Numerous studies reported it was a major human factor to the high risk of the operation errors [10–12]. The counter measure can be achieved by the adaptive automation theory, where a human-centered system is implemented to detect and regulate the mental fatigue by reallocating the functionalities between the operator and the machine [13].

The reliability of such adaptive systems is based on the success recognition of mental fatigue levels. The corresponding indicators mainly include secondary task performance, subjective ratings, and electrophysiological measurements [11]. Neurophysiological signals received increasing attention since they are closely related to the functions of responsible cortical or subcortical networks such as basal forebrain, thalamocortical neurons, and locus coerulus [9]. Among them, electroencephalography (EEG) generated by the summation of the postsynaptic potentials from a wide range of cortical neurons can be quite repeatable and predictive [14]. Besides, the EEG signals can be easily recorded via portable and wireless sensors owning to the progress of the biomedical engineering devices.

1.1. Related works

The relationship between the spectral EEG features and the mental fatigue was revealed in early studies. Grandjean indicated EEG theta (4–7 Hz) rhythm reflected the decrease of the alertness

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during drowsiness and the fatigue [15]. Okogbaa et al. reported the energy of the alpha rhythm (8–13 Hz) increased when the impairment of the sustained attention arose [16]. Markand suggested the alpha rhythm might temporally attenuate and reappear for a few minutes in high fatigue state [17]. Lal and Craig found that the spatial distribution variation of the occipital and parietal alpha wave was the useful indicator [18]. Makeig and Jung reported both of the alpha and theta rhythms were related to the variation of the fatigue level [19]. In recent studies, EEG features of higher sensitivity were abstracted from the conventional spectral power. Simon et al. proposed that the alpha spindle was a more objective clue, which measured the short bursts of the alpha waves [20]. Papadelis et al. employed the alpha relative band ratio in the central and parietal as the mental fatigue indicator [21].

Since various EEG features have been extensively analyzed in the literature, the pattern classifier constructed via machine learning principles were used to further extract and fuse the useful information hidden in those multidimensional variables. Such classifier derives a predictive model for instantaneous mental fatigue estimation. Among these works, the shallow structure based pattern classifiers are employed. Aleksandra et al. extracted cross-spectral density features from EEG and employed learning vector quantization based artificial neural network (ANN) for mental fatigue recognition [22]. Kiymik et al. combined discrete wavelet transformation and ANN classifier to improve the classification performance [23]. Yildiz et al. computed Shannon entropy features from EEG and built an adaptive neural fuzzy inference system to distinguish binary mental fatigue levels [24]. Mervyn et al. used support vector machine (SVM) model to process EEG power generated by fast Fourier transformation [25] and improved the binary fatigue classification rate to 99.3%.

The applications of deep learning methods on neuroimaging datasets have received attention [26] in recent reported works. The deep learning approaches are applied to abstract the high-level EEG features and to build more robust mental fatigue estimators [27]. Different from shallow classifiers such as SVM and single-hidden-layer ANN, deep learning model generates more compact feature abstractions via multilayered, hierarchical networks [28]. In the newest studies, Hajinoroozi et al. developed a channel-wise deep convolutional neural networks (CNN) to predict the driver mental fatigue based on EEG signals [27]. They generalized the conventional CNN model structure by introducing restricted Boltzmann machine between each two hidden layers. In our previous work, we proposed switching deep belief networks (DBN) to cope with the individual differences in EEG signals and constructed a cross-subject mental fatigue classifier [29]. These works exploited the merits of the deep learning in intelligent feature engineering, where the time and frequency domain EEG features were automatically combined to more salient mental fatigue indicators.

1.2. Motivation of the present study

According to the brief literature review, we note that most of the existing studies on mental fatigue recognition were task specific. That is, the classifier was trained and validated via the EEG datasets recorded from exactly the same human–machine task. However, the pattern of the mental fatigue stimuli for EEG signals cannot be always the same in real-world environment, e.g. the speed of the driver fatigue accumulation could vary on different traffic status. Therefore, it is crucial to improve the generalization capability of a task-generic, mental-fatigue classifier constructed by the EEG data from a typical task and tested on different one. Such cross-task OFS recognition issue on the dimension of mental workload has been investigated via shallow learning approaches [30,31]. These works showed the huge volume of historical EEG data could be transferred and adaptively used for predicting novel mental stimuli via proper machine learning approaches.

Since the task-generic mental fatigue recognition received much less attention in the literature, this study attempts to address this issue by employing the deep classifier. The critical motivation behind is that task-generic classifier facilitates sufficient and transferable EEG data in the training stage, which has the capability to prevent the overfitting from the deep network with numerous parameters for tuning. It can be thus expected to maximally exploit the advantage of the deep model for high efficiency of feature abstraction or feature denoising.

To achieve the transferability of the EEG data across different fatigue stimuli, the hierarchical extreme learning machine (H-ELM) has been employed as the basis for the task-generic classifier [32]. Different from the stacked autoencoder (SAE) and DBN based deep learning primitives, H-ELM is generalized from ELM, a high-speed learning machine proposed by Huang et al., which does not require the gradient-based optimization for both of the pre-training and fine-tuning on network weights [33,34]. Such mechanism significantly reduces the time cost for training and further facilitates the real-time weight updating to tackle the distribution variation of the novel EEG data. Inspired by this, we specifically design a dynamical deep extreme learning machine (DD-ELM) for coping with the task-generic mental fatigue recognition issue. The essential of the DD-ELM is to dynamically recompute part of the weights of the deep ELM by using the unsupervised transfer learning principle. The values of the weights at current time step is determined based on the historical EEG feature abstractions. We examine the performance of the DD-ELM by two well-controlled experimental paradigms via Auto CAMS platform with different mental fatigue stimuli.

The application of the ELM is very promising for the data-driven modeling because of its universal approximation capability. The related theory was proofed by Huang et al. [35]. In detail, the ELM network is a universal approximator when users simply choose randomly neuron parameters in the hidden layer where the activation function can be any type of bounded non-constant piecewise continuous functions. It ensures the proposed mental fatigue classifier has the capability to fit the complex distribution of the psycho-physiological data. Moreover, the classification capability of ELM with high generalizability has been also shown in [34], where the maximal margin optimization has been introduced with the regularization term for the output weight vector of the ELM model. To this end, the ELM shares the merits of the SVM classifier since both of the two methods minimizes the norm of the weight vector to control the over-fitting.

In particular, the ELM approach has been shown as an efficient tool to analyze the neuroimaging data in recent studies. In [36], Lu et al. proposed a hybrid model that combines the 2D discrete wavelet transformation and the ELM optimized by the bat algorithm to classify the magnetic resonance data. In their work, the ELM was used as an auto-detector for pathological diseases of the brain functionality. By incorporating the 10-fold cross validation, 98.33% overall classification accuracy was achieved on 132 instances. In [37], Zhang et al. developed a framework for smart pathological brain detection by applying a synthetic minority oversampling, wavelet packet Tsallis entropy, extreme learning machine, and Jaya algorithm. Their work showed competitive classification rate of $99.57 \pm 0.57\%$. Both of the two works strongly supported the classification capability of the ELM model.

The rest of the paper is organized as follows. The paradigms of two different human–machine tasks and the derived EEG datasets are described in Section 2. In Section 3, the DD-ELM algorithms are presented in detail. Section 4 summarizes the task-generic classification results across DD-ELM and several state-of-the-art fatigue estimators. The merits and the limitations of the DD-ELM are