Research Article

Classification Mental Workload Levels from EEG Signals with 1D Convolutional Neural Network

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Abstract

Mental workload (MWL) can be estimated according to the state of cognitive capacity after an activity. In this study, it is aimed to classify MWL levels from Electroencephalogram (EEG) signals recorded from a task moment. Using the proposed one-dimensional convolutional neural network (1D-CNN) model in the study, low (L) and high (H) level WL states were classified. The classification process was carried out in two stages. EEG signals passed through the preprocessing stage were classified with 1D-CNN in the first stage. In the second step, these signals were decomposed into subbands by applying Empirical Mode Decomposition (EMD) and classified with 1D-CNN. As a result of the classification process, accuracy (Acc), sensitivity (Sens), and specificity (Spe) values were obtained and evaluated in this study. As a result of the evaluation, the most successful Acc rate was 98.4%, Sens rate 97.62%, and Spe rate 98.94%.

Keywords: Electroencephalogram, Mental Workload, Convolutional Neural Network.

1. Introduction

MWL is defined as the load created by the mental or perceptual activities required to complete a particular task [1]. MWL, which significantly affects user performance, is used in many areas such as brain-computer interface (BCI) and evaluation of driving systems [1, 2]. Evaluation of MWL is very important for the analysis of brain functions [3]. Although measurements are made by questionnaire for MWL evaluation, many physiological measurement methods are also used [3, 4]. EEG measurements are used more frequently for MWL, which requires mental strength and is directly related to electrical activities and brain functions [2, 5]. EEG is a low-cost neuroimaging technique that measures and records the electrical potential resulting from brain activity and is used to test the cognitive process [6]. Thanks to the electrodes placed on the scalp, EEG recording is made by measuring the electrical potentials in the brain.

Studies based on various methods of signaling in the evaluation of MWL have been conducted. In their study, Qu et al. [7] applied independent component analysis to EEG signals and classified the power spectral densities with Support Vector Machines (SVM), and distinguished the MWL level with a success rate of 79.8%. In another study they conducted [8], they proposed an MWL classification method based on the Cross-Session Subspace Alignment (CSSA) method. As a result of the method they suggested, the highest success rate was obtained with SVM at 84.7%. In another study on MWL, Aydın [9] obtained features in fractal dimensions from EEG signals, and as a result of his experiments, he was able to separate the MWL level into three parts (low-medium-high) with the SVM classifier at the rate of 95.39% in the most successful way. In their study, Singh et al. [10] obtained an 88.88% success rate by using an SVM classifier by extracting features from the time domain in EEG signals to distinguish MWL levels in two parts (L-H).

A few studies evaluating MWL using machine learning classifiers have been mentioned above. Recently, it has been noted that higher success rates can be obtained from raw data by using the automatic feature extraction advantage of CNN [11, 12]. Although CNN is frequently used in BCI studies, it has been emphasized that there is a lack of work in MWL-level decomposed and classification [12]. In this study, it is aimed to distinguish the 1D-CNN classifier and MWL (L-H) by decomposed the EEG signals recorded during the activity into subbands using the EMD method. EEG signals were successfully decomposed into subbands by the EMD method and data augmentation was achieved before the classification. Considering the results obtained in similar studies in the literature, it is aimed to increase the preferred performance criteria in the evaluation of this study. The block diagram summarizing this work is given in Figure 1.

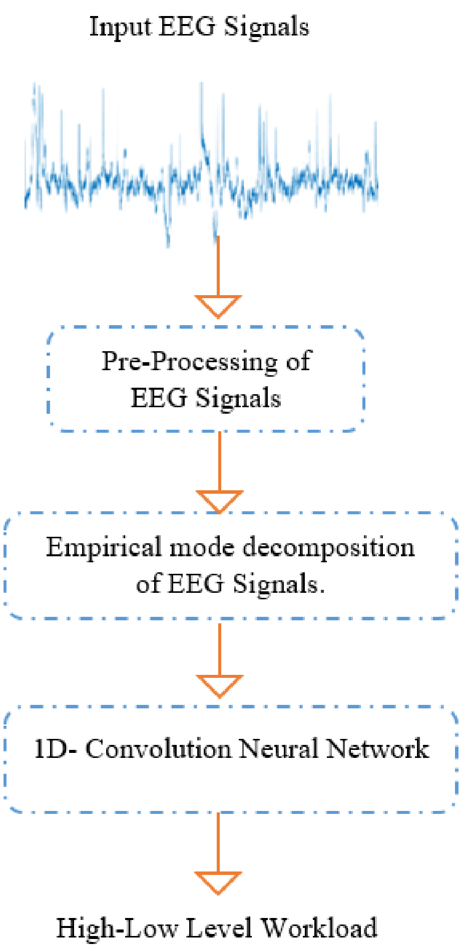

Figure 1. Flow chart of the proposed work

2. Methodology

2.1. Dataset and Experiment Description

EEG signals shared by Lim et al. were used in the study [13]. EEG signals were recorded while 48 participants were used, and all participants were male. EEG signals were obtained from 14 channels ("AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4") with 128 Hz sampling frequency using the Emotiv EPOC EEG system. The Simultaneous Capacity (SIMKAP) test module of the Vienna Test System, which is a psychological test used to evaluate the multitasking and stress tolerance of individuals, was applied to the participants as an experimental set [13, 14]. The interface of the applied experimental set is given in Figure 2. While answering the questions asked to them, the participants are asked to match the objects from the panel at the same time.

The experiment consists of two sessions, the resting state, and the MWL level. In the first session, no task was given to the participants and they were asked to rest with their eyes open. In the second session of the experiment, the SIMKAP test module given in Figure 1 was applied. A 2.5-minute EEG recording was used for the evaluation of MWL. At the end of the experiment, a questionnaire was presented to the participants to evaluate their workload level. In this study, the results of the survey were divided into two groups low workload (4-6) and high workload (7-9) levels, and the signals obtained from these groups were used. Detailed information about the data set and experimental stages it is given in Ref [13].

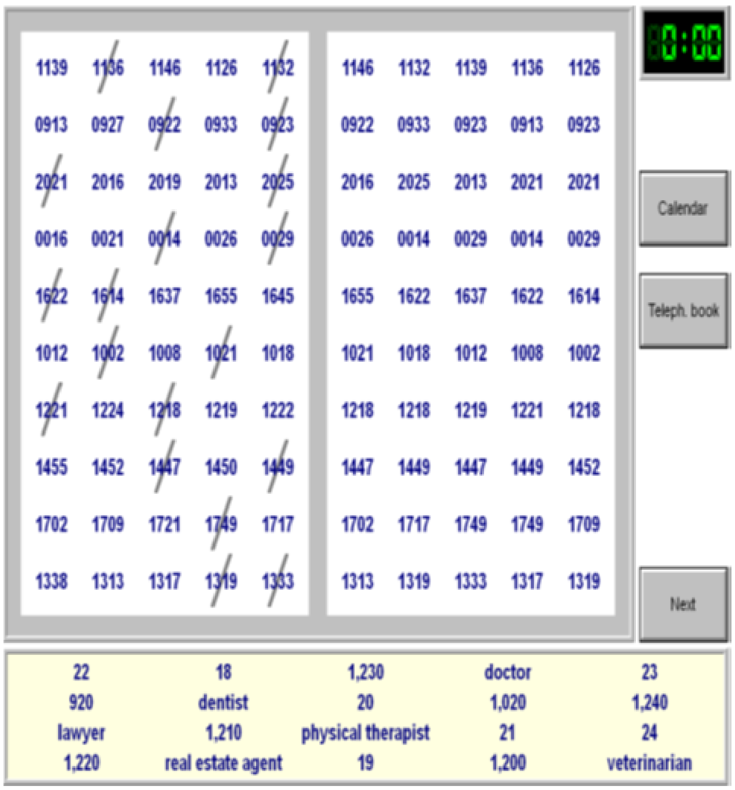

Figure 2. SIMKAP multitasking test module [13]

2.2. Pre-Processing of Raw EEG Data

While recording EEG signals, power line interference and voluntary or involuntary movements of the patient may cause noise on the signal. A 0.4-30 Hz band-pass (FIR) filter were applied to clean the noise of the EEG signals used in the study. After filtering, approximately 2.5 minutes (19200 samples) of non-overlapping EEG signals were divided into 2 parts of equal length. In this way, our data number has been increased by applying the segmentation process, which is preferred in studies to increase the number of data in signals that are few. Example EEG signals of MWL levels used in the study are given in Figure 3.

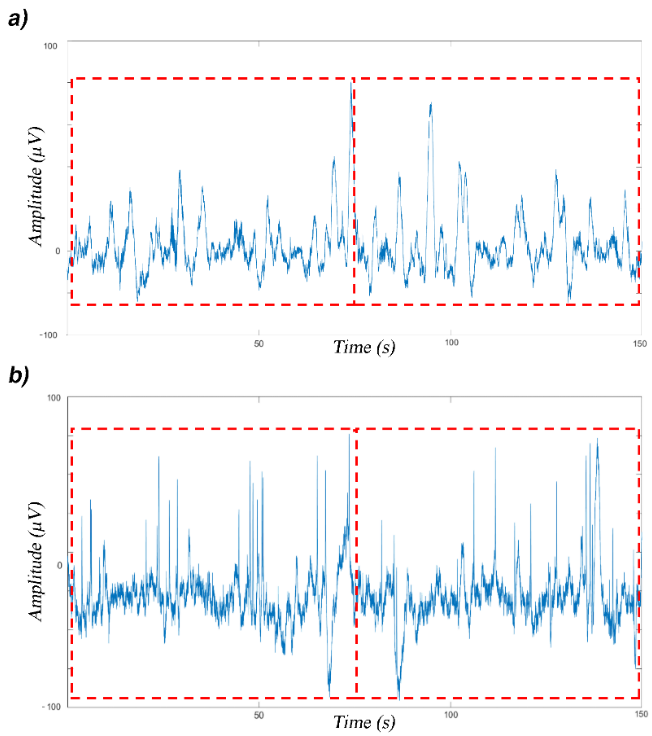

Figure 3. (a) L-WL Sample EEG signal, (b) H-WL Sample EEG signal

2.3. Empirical Mode Decomposition Method

The EMD method proposed by Huang et al. is widely used to analyze non-stationary signals [15]. In the EMD method, it is accepted that there may be different simultaneous oscillations in the signals at the same time, depending on the complexity. A complex signal can be decomposed into more stationary subbands by the EMD method. Subband components are known as intrinsic mode functions (IMF). The EMD method has been used in many physiological signal studies to both decompose signals and remove noise [16]. Detailed information about the EMD method can be found in ref [15, 16]. The level of decomposition was chosen according to the stopping criterion. In this study, EEG signals were evaluated by dividing them into 6 subbands by the EMD method.

2.4. Proposed 1D CNN Model

CNN is a widely used machine learning model inspired by the biological nervous system [17]. In the CNN model, there is no need for extra feature extraction from the learning phase. CNN can learn directly from data. Thanks to this advantage, it is frequently preferred in studies [11]. With CNN, one-dimensional non-image data such as signals and sounds can be processed, and it has been successfully applied in the analysis of EEG signals [12, 18]. CNN has a structure that can consist of several layers. These layers are the convolution layer, the nonlinear layer, the pooling layer, and the fully connected layer [18]. Thanks to the 1D-CNN model proposed in this study, automatic classification of EEG signals is provided without any feature extraction. For the proposed model, the ReLU function, which is one of the most useful activation functions, has been preferred. The CNN was trained using Adam optimizer. The maximum number of periods for training is set to 20 and the mini-batch size to 64. The architecture of the proposed 1D-CNN model is given in Figure 4.

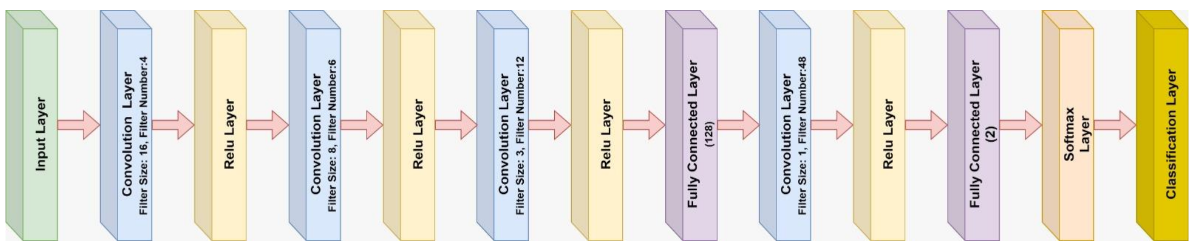

Figure 4. Proposed CNN Model Architecture

2.5. Classification and Performance Measures

In this study, MWL levels (L-H) were classified using the 1D-CNN algorithm from the EEG signals recorded during mental activity. During the classification process, different parameters and layers were applied many times to create the model with the most successful performance. In the first condition cleared from the noise by preprocessing, and in the second condition, using the EEG signals that were decomposed into their subbands (IMF 1-6) by the EMD method. In the classification process, a total of 1260 EEG signals were used as data in the first condition. In condition 2, a total of 7560 EEG signals were used as data. In both conditions, data is reserved for classification using 5-fold cross-validation as 80% training and %20 test data, as is done in studies based on classification processes. Detailed information about the data used is given in Table 1. As a result of the classification process, Acc, Sens, Spe values were obtained and evaluated. Acc, Sens, Spe., the formulas and explanations of the values are given in Table 2 [19].

Table 1. Number of data used in the study

Condition	Number of Subjects	Number of channels	Segmentation	Total Number of Data
1. L-H WL	45	14	2	1260
2. L-H WL EMD	45	14	2×6 subbands	7560

Table 2. Performance metric formulas and explanations number of data used in the study

Metric	Formulas	Explanation
Accuracy	$\frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)}$	Accuracy is overall performance of model
Sensitivity	$\frac{TP}{TP + FN}$	Sensitivity is the rate at which it can detect those who carry the disease.
Specificity	$\frac{TN}{TN + FP}$	Specificity refers to the rate at which someone who is not sick is correctly diagnosed.

3. Experimental Results

In this study, it was aimed to distinguish MWL levels (L-H) using EEG signals, and for this purpose, EEG signals were evaluated and classified with the proposed 1D-CNN algorithm. The classification process was carried out for two conditions. In the first condition, preprocessed and divided into 2 parts EEG signals were evaluated, in the second condition, these EEG signals were decomposed into subbands by the EMD method.

Before the classification process took place, 80% of the data was separated as training data and 20% was test data and evaluated according to CV-5. In addition in this study, evaluation was made by performing the classification process using the hold-out technique. As a result of the classification process, Acc, Sens, Spe values were obtained for each fold. The results obtained for both conditions and each fold are given in Table 3-4, and the average results for comparison are given in Figure 5. In this study, 20% of the total data was evaluated by considering it as a random data from the proposed model without going through both the training and testing phases (hold-out). The classifier results obtained for both cases are given in Figure 6.

Table 3. Condition 1 (L-H WL) results

Fold number	Acc (%)	Sens (%)	Spe (%)
Fold-1	98.1	99.0	97.2
Fold-2	100	100	100
Fold-3	95.3	91.3	99.1
Fold-4	98.6	97.8	99.2
Fold-5	100	100	99.2

Table 4. Condition 2 (L-H WL-EMD) results

Fold number	Acc (%)	Sens (%)	Spe (%)
Fold-1	82.6	100	75.8
Fold-2	96.2	97.1	95.4
Fold-3	97.8	98.4	97.8
Fold-4	95.8	97.8	94.4
Fold-5	89.7	93.6	87.4

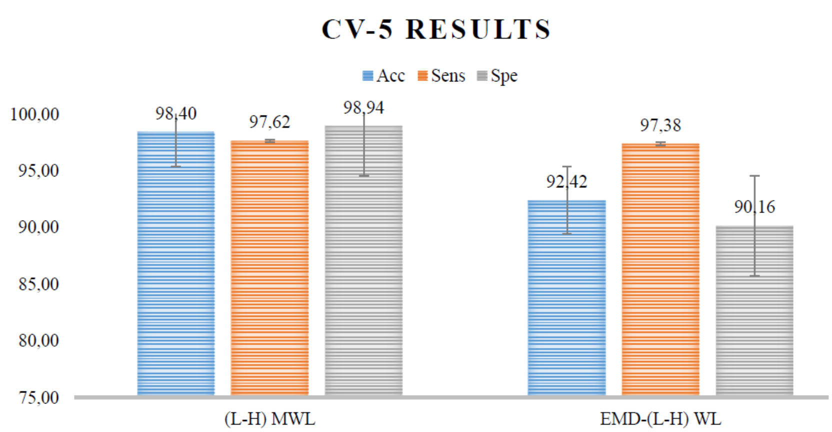

Figure 5. (CV-5) Classifier average results

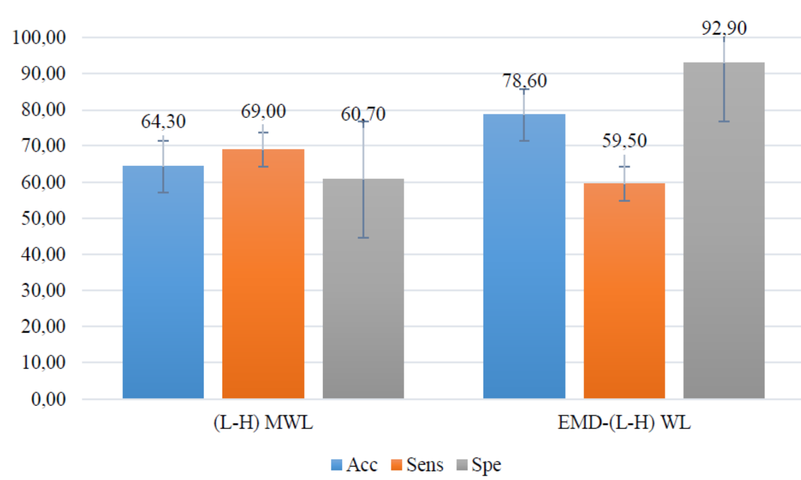

Figure 6. (Hold-out) Classifier average results

4. Discussion and Conclusion

In this study, it is aimed to classify MWL levels from EEG signals recorded during a given task with the 1D-CNN model. For this purpose, the noise of the EEG signals was cleaned by preprocessing. The noise-free EEG signals are divided into 2 equal-length segments by segmentation. EEG signals were classified with 1D-CNN in two states. In the first condition, the classification process was carried out without applying any signal processing method to the preprocessed EEG signals. In the second condition, EEG signals were decomposed into subbands by the EMD method, and classification was performed. Acc, Sen, and Spe values were obtained as a result of the examination made in both conditions. As a result of the study, the most successful classification results were obtained in the 1st condition. The success rate of the model was evaluated by including 20% of the data used in this study into the classifier as a random data. As a result of the evaluation, it was seen that the success rate of the proposed model increased when it was decomposed into its subbands by EMD. In a similar study with the data set used in the study, this rate was found to be 42.4% [13].

In Table 5, success rates obtained in sample studies that classify MWL levels using the same data set are given for comparison with the success rate in this study. In some of these studies, the classification process was carried out with machine learning while deep learning models were preferred them. When Table 5 is examined, it is seen that this study is more successful than similar studies conducted without using the EMD method. In order to increase the number of EEG signals applied to the classifier, the EMD method was preferred in this study. However, it has been observed that the application of the EMD method reduces the success rate compared to the raw form.

Table 5. Comparing the results of studies using similar datasets

Study	Workload Task Levels	Feature Extraction	Classifier Model	Acc (%)
Aydın [9]	Low-Medium-High	Katz's- Higuchi's fractal dimension	SVM	69
Lim et al. [13]	Low-Medium-High	Power spectral density	SVM	95.39
Kingphai and Moshfeghi [19]	Resting-MWL Low- High	Fast fourier transformation	Hybrid Deep Neural Networks	95.9 84.56
Chakladar et al. [20]	Resting-MWL Low-Medium-High	Power spectral density	Hybrid Deep Neural Networks	86.33 82.57
Proposed Study	**Low-High** Low-High-EMD	**EMD**	**1D-CNN**	**98.4** 92.42

As can be seen in Table 5, it is possible to achieve high classification success by using different classifiers and methods. In this study, a new method using the EMD method and 1D CNN model is proposed to distinguish MWL levels. In studies with deep learning models, it is desired to have a large number of data. In this study, to increase the number of data, segmentation of equal length was applied to the EEG signals and also decomposed into subbands using the EMD method. It has been seen that the results obtained are successful compared to the case studies using similar data sets. In future studies, the number of data can be increased by using different signal processing methods and different classification models can be tried to improve the success rate.

5. Acknowledge

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