Mathematical Statistician and Engineering Applications
ISSN: 2326-9865
DOI: https://doi.org/10.17762/msea.v70i1.2293

Machine Learning Techniques in the Detection of Drowsiness in Drivers

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Article Info
Page Number: 139-146
Publication Issue:
Vol. 70 No. 1 (2021)

Abstract
Drowsiness is one of the major risk factors that contributes to numerous accidents. With a variety of strategies and accurate categorization procedures that identify different drowsy stages and alert the individual at particular periods, this study seeks to lessen its effects. To improve the detection effectiveness of the current methods, Fractional Fourier Transform (FrFT) has been employed for feature extraction, ABC (Artificial Bee Colony) for optimisation, and NN and sparse classifiers for classification. The two solutions exhibit high efficiency when it comes to improving the system's accuracy and other performance measures. The two strategies are also contrasted, with the latter producing better results.

Article History
Article Received: 25 January 2021
Revised: 24 February 2021
Accepted: 15 March 2021

Keywords : Electroencephalogram (EEG), ROC, drowsiness detection, feature extraction, Neural Network(NN) classifier;FrFT;ABC;Sparse classifier.

I. Introduction

Achievable difficulty within the again of traffic accidents is implied to cause pressure of drowsiness. The Nationwide Highway website online visitors Safety Inspection (NHTSA) advised in 2002 that in the moreover ten years about zero.7% of drivers were concerned in an accident that they function too sleepy with [1]. The Nationwide Sleep Basis (NSF) furthermore quantified that a massive fifty one% of person drivers had driven a car in drowsiness and 17% had felt asleep [2].The EEG signal is an additionally mobile contemporary because of the cerebral interest of the mind and are primarily known as alpha, beta, theta and delta waves [3]. The EEG signal is utilised to research the consciousness hobby and is extensively utilised. Brain sports are characterised by their frequency, amplitude and responsiveness. Delta waves recorded by electroencephalogram (EEG) [4] are usually associated with slow-wave sleep (SWS), which is a useful tool for characterising sleep depth. When thinking of sleepiness, only the delta wave is considered, which can be sleep waves whose frequency can be very low, ranging from 0.5to 2 Hz [5]. Physical and physiological adjustments of human activities cause sleepiness [6]. In addition, there are numerous factors that affect cognitive state: sleepiness, fatigue, monotony, psychophysiological characteristics, and distraction [7]. The primary goal of this work is 1) to develop a unique method for distinguishing remarkable levels of sleepiness based primarily on EEG alerts recorded at the same time subjects were asleep. 2) Improving class accuracy through the desire for a better optimization technique. 3) And facilitate the computation by first-class classifier selection. Thus, 3 inexperienced remodel based completely characteristic extraction methods are proposed together aspect a comparative have a look at their statistical functions and positioned that the overall performance of the device in lowering the time required for the

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computation of each method is to be developed in nature.

II. Technique implemented

The work aims to maximize the accuracy of sleepiness-related statistics obtained from the sleep database. The common block diagram created for the three feature extraction strategies is shown in Determination 1, which shows the steps of character processing, feature extraction, optimization, and classification. The first step is to acquire indicators from the database that will be used to build the model. The uncooked EEG signal is generated from the database. The extracted signal is preprocessed using low-bypass median cleaning, which passes the low-frequency sleep waves and attenuates the overfrequency signals. The processed signal is decomposed into a kind of samples with the required period, then the function extraction methods are completed and finally the optimality is determined. The resulting output is discovered via the type of sophistication to locate the sleepiness. Moreover, the overall performance of the device is found to be improved in reducing the computation time.

III. EEG DATABASE

The first and most important step is the collection of EEG data, which allows accurate classification of the results. Training sets are collected from sleepy subjects and these data sets are obtained from the Internet [8]. The EEG data are obtained from the Sleep-EDF database in EDF format [Sleep Recordings and Hypnograms in European Data Format (EDF)]. Sleepiness state varies among subjects according to somatic state. A common frequency of Hz is chosen for all subjects.

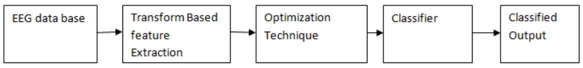

Figure 1. Basic Block diagram

IV. GENERATION OF RAW EEG SIGNAL

A bendable format for the trade and garage of organic and bodily multichannel signals is eu statistics layout (EDF). EDF is mainly used in the planned programs of sleep analysis algorithms. Any database that is downloaded is an EDF file that can not be understood since it is a direct record of the radio telemetry system. In order for the document to be converted to a readable format, the EDF document must be converted to the ASCII file. This is done with the help of the EDF converter.

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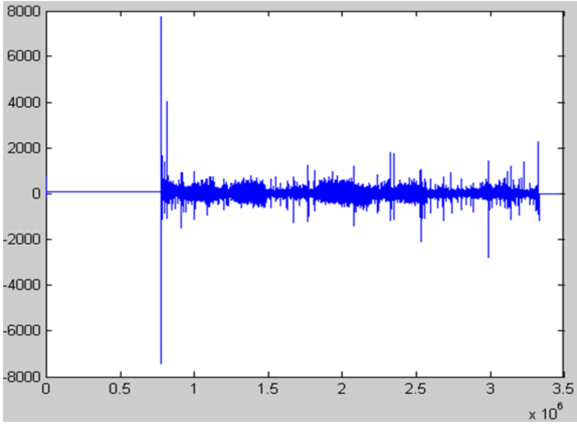

Figure 2 .Generated Raw EEG signal

Parent 2 represents the EEG, the uncooked signal was generated ready for feature extraction. In addition, the generated EEG signal was found to contain artifacts and noise generated by normal human sport. Since the organic alarm signals are low frequency signals, low-skip median cleaning is sufficient to attenuate the artifacts and noise. Figure 3 shows the noise-free preprocessed EEG signal, i.e., the analyzed signal that can be subjected to the post-processing primarily based feature extraction strategies

V. FEATURE EXTRACTION AND CLASSIFICATION METHODS

METHOD-1: Fractional Fourier transform based feature extraction without feature selection using the Neural Network Classifier (FrFTNN):

A. Fractional Fourier Transform:

The fractional Fourier transform, often known as the FrFT, is a member of a class of time-frequency expressions that are utilised widely in the field of signal processing. Assuming that the signal x(t) is represented along the time axis and its ordinary Fourier transform f, i.e., x(, is represented along the frequency axis, the Fourier transform is consistent with some of the observed properties of the Fourier transform[10-11]. An inversion of the right time axis results from two consecutive rotations of the signal by π/2. Furthermore, the signal remains unchanged for four consecutive rotations, so a rotation of the signal by 2π should leave the signal unchanged. The FrFT is a linear operator and corresponds to the rotation of the signal by an angle that is not a multiple of π/2. F is a T-transformation of f and thus another transformation that can be redefined as follows:

$$T^{\alpha}\{f(x)\} = F_{\alpha}(u) \qquad (1)$$

T^{α} here is called the "α-order fractional T transform" and the parameter α is called the "fractional order".

Filtering and noise reduction in the fractional domain is the most important feature that makes it more efficient than the previously discussed WPT. Here, FRFT acts as a multiresolution filter and also exhibits high frequency resolution in 3D analysis of the EEG signal compared to WPT. Noise removal is not possible with conventional filtering in the

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frequency domain. However, we can rotate the Wigner distribution, i.e., perform the fractional Fourier transform, and then filter out the unwanted noise. By choosing the right rotation angle and iteratively performing the same process, we can easily remove the noise, as shown in Figure 6.

The α^{th} order Fractional Fourier Transform operation corresponds to $\emptyset = \alpha\frac{\pi}{2}$ rotating the Wigner Distribution by an angle in the clockwise direction, so that the noise and signal do not overlap. Then we can rotate the Wigner distribution [11], i.e., perform the fractional Fourier transform, and then philtre out the unwanted noise. First, the EEG signal is acquired and filtered to obtain an analysed signal. From the 3000 samples, only 1500 samples are still selected for our consideration, and these 1500 samples are divided into five features with 300 samples each. This is how the feature assignment is done. The selected sampling frequency is 100 Hz. Next, each selected feature is subjected to a short-time fractional Fourier transform. The fractional power can take any value on the order of 0.001 between 0 and 1. The importance of using the fractional short-time Fourier transform is that high fractional frequency resolution and time resolution can be achieved, and any signal change within a short period of time can be analysed with ease and precision. Feature extraction is performed by calculating the logarithmic energy values of the transformed feature sets. The logarithmic energy equation is given by

$$E_{\Omega_{j,k}} = \log\left(\sum \frac{n(W_{x,u}^{T}\ X)^2}{\frac{N}{2^x}}\right) \qquad (2)$$

and this gives the normalized logarithmic energy of the fractional fourier transform coefficients extracted from the subspace $\Omega_{x,u}$ Fractional Fourier transformed signal is given by $W_{x,u}X$ and they are simply the coefficients and they are evaluated at subspace $\Omega_{x,u}$ and $\frac{N}{2^x}$ is the number of coefficients in that particular subspace. After calculating the energy value of the features, classification is performed using an NN classifier with backpropagation learning.

B. Classification Using NN Classifier with Back Propagation Learning

Neural networks show high tolerance to noisy data and are able to classify samples for which they have not been trained. The best known neural network algorithm is the backpropagation algorithm (BP), which was proposed in the 1980s.

At the beginning of the 1970s, an architecture known as feed-forward back-propagation was devised. This synergistically generated BP design is now the model for complex, multilayer networks that is the most popular, practical, and easy-to-learn model available. The fact that it offers non-linear answers to issues that aren't always well defined is one of its greatest strengths. There is at least one hidden layer within the network, in addition to an input layer and an output layer.

During the learning phase, the network proceeds in the forward direction, and the outcome of each element is generated layer by layer. This often involves adjusting the second derivative of the transfer function, and connections and weights are typically updated making use of the delta rule [9], [12]. This process continues layer by layer until the input layer is reached. This is where supervised learning is implemented. In this work, two hidden layers are chosen to reduce the complexity and the outputs obtained are the desired classes, namely awake, slightly sleepy, moderately sleepy, fairly sleepy and very sleepy. So based on the comparison between the training data and the test data, the desired states are classified.

Considered here is a feed-forward network consisting of n input units and m output units. It is possible for there to be a multitude of hidden units, and these hidden units can have any kind of feed-forward connection pattern required. A training set of samples, also known as input and output patterns, is obtained by us as well. This set of samples is composed of p ordered pairs with n and m-dimensional vectors. This network generates an output oi that is typically distinct from the target ti when it is given an input pattern consisting of samples xi taken from the training set. The objective is to determine the specific level of drowsiness that the person possesses. Using the BP learning algorithm, our objective is to determine whether or not oi and ti for all values of i from 1 to p are the same. Additionally, we want to reduce the error function of the network, which is described as

$$E = \frac{1}{2}\sum_{i=1}^{p} ||oi - ti||^{2} \qquad (3)$$

Once this function has been minimised for the set that is being trained, the network will be given brand-fresh inputs for which there is no previous data, and we will anticipate that it will interpolate. The network needs to determine whether an unfamiliar input vector matches the previously learned patterns and generates an output that is comparable to previous results. Finding a local minimum of an error function can be accomplished with the help of the backpropagation method [9], [12], [13]. The weights for the mesh are picked at random before the mesh is initialised. The initial weights can be corrected with greater certainty by determining the gradient of the error function. Our mission is to perform recursive computations on this gradient and then, finally, to find a balance between it and the objective. Thus, the sleepiness that is different is classified.

Method-2 - Fractional Fourier Transform based feature extraction with ABC optimization (feature selection) using Sparse Classifier (FrFTABCS):

A. Fractional Fourier Transform:

As mentioned earlier, FrFT is used here and the optimization is done artificially, i.e., using the Bee algorithm (ABC).

B. ABC Feature Selection Algorithm:

After calculating the logarithmic energy values of the features, the next step is to select the best features that match the desired classes, i.e., awake, slightly sleepy, moderately sleepy, rather sleepy, and very sleepy. The bee colony has experience in searching for its food. Therefore, it is able to memorize all the characteristics of the collected food. This form of bee intelligence, known as the swarm, makes use of the primary means by which bees share information with one another. They make use of a variety of techniques, including as the tail dance, which assists in the optimisation of the identification of food sources and the search for new ones. By doing this tail dance, the worker bee is able to communicate with her fellow bees regarding the location, proximity, and quality of available food. The bees modify their search strategies in accordance with the information that is passed on so that they can locate food of high quality while ignoring food of lower quality. Because of this, they are an excellent choice for the development of a new intelligent search algorithm, which will be referred to as the ABC algorithm. It is an extremely straightforward stochastic optimisation approach that is built on top of a population [14, 15]. In the ABC algorithm, the bee colony is made up of two distinct types of bees, which are referred to as scout bees and worker bees. The mission of discovering a new source of food is carried out by the scout bees. Employed bees have the responsibility of locating a food source that is within a quarter of the total number of food sources stored in their memories and communicating this information to other bees.

C. Sparse Classifier:

There is no guarantee that the classes of features optimized in this way have been correctly separated, because the classification of optimized features is uncertain. Such class imbalance problems can be handled with a sparse classifier. Sparse classifiers output faithful conditional probabilities near the decision boundary [16].

Cascade classifiers such as neural network classifiers have many drawbacks in both the training and testing phases. The training process requires a lot of manual tuning of the control parameters, and it is non-trivial how to manage the tradeoff between the performance and complexity of the cascade [17].

After creating the optimal feature sets, we proceed to classification by using a sparse classifier. It is used to check the separated classes to see if elements of a given set occur only in that set and not in other sets [18], [19], [20]. If so, it is correctly classified into that particular set. Intra-similarity between samples in a given class is an increasing function and inter-similarity between two classes is a decreasing function in this way.

VI. RESULTS AND DISCUSSION

The computation time may be different for different processors. A ROC curve is constructed to determine the efficiency of the implemented mechanism. The ROC curve is plotted between the true positive rate (TPR) and the false positive rate (FPR). The curve created using ROC indicates the exact efficiency of the proposed method. The ROC curve was created to determine the classification accuracy considering 54 sleepy and 32 awake test samples.

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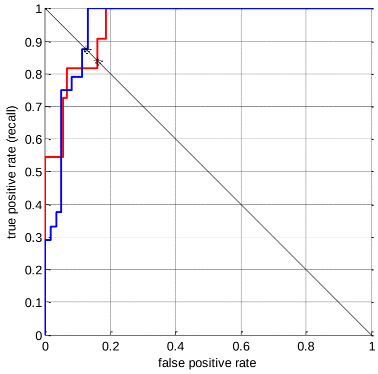

Figure 4. ROC of the two methods

(Blue - Method 2, Red - Method 1) The classification accuracy of the two methods is in the order that the Sparse classifier ascends with a maximum of 89.84%, which can be seen from the confusion diagram.

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