

Research Article

Detection of the Driver's Mental Workload Level in Smart and Autonomous Systems Using Physiological Signals

Dan Wang, Yier Lin , Liang Hong, Ce Zhang, Yajie Bai, and Zhen Zhen Bi

School of Mechanical Engineering, Tianjin University of Science and Technology, Tianjin, China

Correspondence should be addressed to Yier Lin; yier.lin@tust.edu.cn

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With the continuous advancement of automation technology, autonomous driving assistance systems are gradually sharing the tasks during driving, but the driver still assumes the main driving tasks. In addition to driving activities, the advent of numerous new functions will have an indirect impact on the driver's mental effort. However, determining the driver's mental effort remains a difficult issue. In this paper, a method is proposed to assess the mental workload of drivers, combining real driver's physiological data with the speed of his/her vehicle. The correlation coefficient and significance level are obtained by analyzing the correlation between physiological data and road types. The relevant data is then preprocessed to determine the characteristic index, with the mental workload as the input index. The driver's mental workload is classified and the mental workload prediction model is constructed on the basis of the combination of the Fuzzy Pattern Recognition Algorithm and Genetic Algorithm. At the same time, the suggested approach is compared to the J48 Classification Algorithm and the Simulated Annealing Optimization Algorithm. The results demonstrate that the proposed method in this paper's effectiveness for identifying the driver's mental workload level is evidently better than other algorithms, which provides new theoretical support for assessing the L3+ driver's mental workload level under the background of the safety of the intended functionality when they take over the control of the drive.

1. Introduction

The workload is a multifaceted term that includes job needs, time constraints, the operator's ability and effort, behavioral performance, and a variety of other elements. It is mostly a measure of how much a person's information processing system is used at work. Measuring a driver's mental effort is a crucial factor in determining his or her driving abilities. Despite the fact that driving a car is a driver's primary responsibility, most modern drivers are also engaged in a variety of nondriving activities while on the road. These responsibilities include not only driving but also the safety of the vehicle, the drivers, and the environment, as well as information, amusement, and communication, which are also factors affecting the driver's mental workload [1]. Mental workload is related to driving tasks and individual differences between drivers. With the same driving task, the mental workload experienced by drivers is not the same.

Driving experience, driving motivation, processing strategy, and driver fatigue state all affect the mental workload level of drivers [2]. For example, on a crowded highway, the driver may be more stressed than driving on empty roads. Another affecting aspect is the driver's overall state, which might be caused by time constraints, news affairs, or the driver's mood. These factors may increase the driver's mental workload and interfere with the driving task. Due to the continuous improvement of intelligent vehicle automation human-machine interface design and driving automation, the information processing faced by the driver becomes more and more strict, which increases the mental workload of drivers, resulting in errors in driver information acquisition, analysis, and decision-making. Research on automation can ease the driver's mental workload and reduce the need for limited attention resources [1]. The methods of evaluating mental workload include subjective evaluation, main task measurement, auxiliary task quantity, and

biological dimension [3]. The subjective evaluation method is the most popular and simplest mental workload evaluation method. The individual estimation method can be divided into the Subjective Workload Assessment Technique (SWAT) scale, the National Association of Scale Aeromodelers-Task Load Index (NASA-TLX) scale, and so on. NASA-TLX is published by the NASA research center in the United States which includes six projects. NASA-TLX is divided into two parts at first: the whole workload is divided into six subjective subjects, each of which is displayed on a blank sheet and works as part of the cognitive questioning requirements, physical duties, temporal needs, effectiveness, effort, and support quantity [4, 5]. Using the questionnaire to assess the user's task load is one of the early methods of NASA's task load index. It was later dubbed the driver activity load index [6] by Pauzie in the mobility sector.

The main task measurement method is divided into the single-index and multi-index measurement methods. Due to the different operation properties, a widely applicable performance parameter cannot be proposed. Therefore, this method cannot compare the mental workload among drivers. The auxiliary task measurement method requires the driver to do two tasks at the same time. The driver needs to focus on the main task and try to do auxiliary tasks with extra ability. The mental workload of the main task is carried out by the performance of the auxiliary task. The higher the mental burden of the main task, the better, the less the remaining resources, and the weaker the driver's ability to engage in auxiliary tasks. The physiological measurement method has been widely used with more objective and accurate characteristics. It is a real-time and objective way to measure the driver's cognitive activities. The advantage of physiological measurement is that it can provide high sensitivity overall evaluation from low mental load to mental overload [7].

It is very difficult to measure the driver's spiritual load. One of the reasons is that there are too many and complex factors affecting the motorist's mental workload. Because the motorist's intellectual capacity involves many factors, there is no unified standard measurement at present. Nowadays, numerous studies have been carried out to assess mental workload levels. Healey and Picard analyzed the changes of ECG, EDA, EMG, and respiration of drivers in a real driving environment and analyzed the average 5-minute interval data of 24 drivers in three driving scenes of rest, highway, and urban road, respectively. The mental stress of drivers was divided into three levels. Another analysis was carried out by adding auxiliary tasks. The results showed that most drivers' skin electricity and heart rate indicators had a significant effect on mental stress levels [8]. Kim et al. studied the driver's mental load based on EEG signals, collected EEG data by recruiting drivers for real vehicle experiments, studied the change rate of EEG of drivers on different road types, and statistically analyzed the data. The research results found that the driving mental workload was higher than that of straight sections when turning left and right. The workload was higher when passing through the intersection than that of the turning section [9]. The NASA-Task Load Index (NASA-TLX) and electroencephalogram

(EEG) were evaluated on 30 drivers by Abdet al. In relatively complicated and very complex situations, the aging drivers' mean physical demand score was the highest compared to others, scoring 37.25 and 43.50, respectively, according to NASA-TLX ratings. Meanwhile, results for the fluctuation of electroencephalogram signals revealed that scenario complexity had a substantial impact on the RP θ and RP α of channel sites FZPZ and O1O2 [10]. Chihara et al. investigated the use of the one-class support vector machine (OCSVM) anomaly detection approach for assessing mental workload (MWL) during car driving. The participants used a driving simulator (DS) to complete driving activities and the N-back task to manage their MWL. There were five difficulty levels in the N-back challenge, ranging from "none" to "3-back." During the DS driving, eye and head movements were recorded. The gaze angle standard deviation (SD), ocular rotation angle SD, share rate of head movement, and blink frequency all had significant associations with task difficulty, according to the findings. OCSVM's decision boundary was able to detect 95% of high MWL states (i.e., "3-back" states). Furthermore, as the task complexity grew, the absolute value of the distance from the decision boundary increased from "0-back" to "3-back" [11]. Chakladar et al. calculated the workload of human volunteers performing multitasking mental activities. The "STEW" dataset is used for estimating mental effort. "No task" and "concurrent capacity (SIMKAP)-based multitasking activity" are the two tasks in the collection. Using a combination framework consisting of a Grey Wolf Optimizer (GWO) and a deep neural network, different workload levels of the two tasks were assessed. GWO was used to pick out the best features for mental activity. However, for "No task" and "SIMKAP-based multitasking activity," the suggested deep model obtains 86.33 percent and 82.57 percent classification accuracy, respectively [12]. Jafari and colleagues investigated whether physiological, subjective, and performance variables might be used to determine the psychological workload caused by regular and innovative subway operations. In a high-fidelity simulator, 11 subway train operators encountered various driving scenarios. The simulation tasks are separated into two groups: conventional operation (preparation for driving and driving without interruption or emergency) and unconventional operation (dealing with tunnel fires, handling high-density passengers, meeting passengers/technicians on track, and dealing with train failures). Using electrophoresis to monitor and evaluate mental workloads in these tasks [13]. When the driver is under a situation of a high or low level of mental workload for a long time, the chance of driving fatigue state will be increased. Both high and low levels of mental effort can lead to driver error; therefore, it is crucial to keep track of it while driving, eventually leading to traffic accidents. As a result, measuring and assessing the mental stress of the driver while performing the primary driving activities is becoming increasingly crucial in practice, which is conducive in improving the driver's driving performance and maintaining driving safety.

Due to the above analysis, most studies on mental workload assessment are conducted on single physiological data. This paper proposed combining the physiological data

with the vehicle speed to assess the cognitive load of the driver. A classification model is developed for estimating the mental workload of the driver in the different road types. Psychophysiological measurement data and vehicle-related data are collected from the real data to evaluate the mental workload of the driver during actual driving. The vehicle onboard parameter recording system and psychophysiological testing equipment are used to synchronously record the changes in the vehicle state and the physiological parameters of the driver so that the changes in the physiological parameters can accurately correspond to the driving state. Physiological parameters such as ECG and SCR of drivers on different road types are recorded to explore the changes in the mental workload of drivers on different road types. The driver's mental workload is classified and the mental workload prediction model is constructed on the basis of the combination of the Fuzzy Pattern Recognition Algorithm and Genetic Algorithm. At the same time, the proposed algorithm is compared with the Simulated Annealing Optimization Algorithm and the J48 Classification Algorithm. The results demonstrated that the correctness of the suggested method in this study for identifying the driver's mental workload level is evidently better than other algorithms, which provides new theoretical support for assessing the L3+ driver's mental workload level.

The structure of this article is organized as follows. The introduction to genetic algorithm and fuzzy pattern recognition algorithm is presented in Section 2. The data processing and test results of the driver's mental workload evaluation test are explained in Section 3. Finally, section 4 summarizes the paper's main points.

2. Introduction to Genetic Algorithm and Fuzzy Pattern Recognition Algorithm

2.1. Genetic Algorithm. Genetic algorithms are based on natural selection and replication and can be used to solve a variety of random search, optimization, and developmental issues. Meanwhile, because this method is comparable to natural evolution, it can overcome some of the challenges that standard search and optimization algorithms face, particularly when dealing with situations with a high number of parameters and complicated mathematical formulations. The main premise of a genetic algorithm is to use particular rules to code the individuals in a population. This code does crossover and mutation across each chromosome, which is optimized based on the value of the individual's fitness function. The chromosomes with high fitness values are retained by the selection algorithm to produce a new population, after which procedures such as crossover and mutation are utilized to pass on the new population's outstanding features to the next generation population. The optimal solution of the global approximation can be achieved via repeated procedures such as selection crossover and mutation [14]. Roulette Wheel Selection is part of the selection method. The probability of a person being chosen from the population is related to the value of their corresponding fitness function. The following are the steps in the competition selection algorithm: Individuals in the quantity

K people are chosen at random from the community, with $K=2$ being the most common value. The one having the highest level of fitness among the others of the quantity of K is chosen from step one with the assumed probability p . With probability $(1-p)p$, the individual with the second fitness among individuals of the amount of K is selected from step one. With probability $(1-p)2p$, the individual with the second fitness among individuals of the amount of K is selected from step one. The stochastic uniform algorithm includes random uniform distribution and remainder residual, taking the integer part of the fitness value for Roulette Wheel Selection. The crossover algorithm includes the following: scattered: randomly generating a genetic binary vector; single point: single-point hybridization, generating a number (at the position represented by the number, the gene exchange of the two parents will be started); two-point: two-point exchange; and arithmetic: arithmetic average. The mutation function algorithm includes the following: constraint-dependent default, which is related to constraints (Gaussian is used when there is no constraint, and adaptive feasible is used when there is a constraint; Gaussian is selected by Gaussian distribution); uniform; and adaptive feasible. The fitness function is a quantitative description used to describe the pros and cons of individual genes, which is often used to evaluate the excellence of individuals in optimization calculations in genetic algorithms. The design of fitness functions is endowed with an important role in the performance of genetic algorithms. In general, the fitness function is related to the optimal problem's optimal solution, so its design should try to meet the requirements of versatility and avoid repeated modifications to the parameters in the function.

The conversion relationship between the commonly used fitness function and the objective function value of the actual problem mainly consisted of the following two types.

The objective function f to be solved is directly transformed into a fitness function F , which is relatively simple and intuitive [15, 16]. The bound construction method is aimed at the minimum problem, and its fitness function is

$$F = \begin{cases} C_{\max} - ff < C_{\max}, \\ 0, & \text{other,} \end{cases} \quad (1)$$

where is the maximum estimate of C .

When it comes to the problem of finding the maximum value, the fitness function is

$$F = \begin{cases} f + C_{\min}f > C_{\min}, \\ 0, & \text{other,} \end{cases} \quad (2)$$

where is the minimum estimate of F .

2.2. Fuzzy Pattern Recognition Algorithm. Fuzzy pattern recognition is based on fuzzy mathematics, which has only been around for over 40 years since its inception in 1965. The fuzzy concept was introduced by Lotfi Zadeh. Since the inception of fuzzy mathematics, fuzzy pattern recognition has been a prominent academic path of fuzzy applicability research. It is mainly applied in computer image recognition,

radar signal analysis, automatic handwritten text recognition, license plate recognition, classification of various classification information, and other fields.

2.2.1. Basic Concepts of Fuzzy Pattern Recognition.

Definition of fuzzy set: given a fuzzy set A in the universe of X , meaning that for any $x \in X$, a number $\mu_A(x)$ is determined, and $\mu_A(x)$ is called the membership degree of x to fuzzy set A , $\mu_A(x) \in [0, 1]$. Mapping $\mu_A(x): X \rightarrow [0, 1], x \rightarrow \mu_A(x)$. $\mu_A(x)$ is called the membership function of A , and the membership function $\mu_A(x)$ is used to express the degree to which the items in the set A to A are members. The membership degree is the outcome of the membership function. The higher the degree of belonging, the more likely x is to belong to A .

Due to various fuzzy concepts in practical applications, it is difficult to represent all scenarios in practical applications and construct a universal membership function. As a result, there is currently no single criterion for determining membership level.

There are 11 membership functions developed in MATLAB, including double sigmoid membership function, joint Gaussian membership function, Gaussian membership function, double sigmoid output similarity measure, s-shaped membership function, Gaussian membership function, triangular membership function, triangle membership function, and zigzag membership function which are examples of generalized bell-shaped membership functions. The membership function is the foundation of fuzzy control; however, the majority of study on this subject is based on experience and experiment. There is currently no established way of determining the membership function. The three commonly used methods for the selection of membership functions are the fuzzy statistical method, subjective experience method, and neural network method [17–19].

2.2.2. Principle of Fuzzy Pattern Recognition. The principle of fuzzy pattern recognition [20] includes the principle of the maximum degree of membership and the principle of nearest selection. The principle of the maximum degree of membership refers to the method of directly calculating the membership degree of a sample to determine its attribution, which is mainly applied to the identification of individuals. Suppose there are N fuzzy sets A_1, A_2, \dots, A_N in the universe X , and each fuzzy set A_i has a membership function $\mu_{A_i}(x)$; then, for any $x \in X$, if there is

$$\mu_{A_i}(x) = \max[\mu_{A_1}(x), \mu_{A_2}(x), \dots, \mu_{A_N}(x)], \quad (3)$$

then, it is said that it belongs to A_i .

The principle of nearest selection refers to that there are n fuzzy subsets A_1, A_2, \dots, A_n , of known categories in the universe X , if $i \in \{1, 2, \dots, n\}$, such that

$$\sigma(B, A_i) = \text{Max}\sigma(B, A_j), \quad (4)$$

where $\sigma(A, B) = 1 - C[d(A, B)]^d$, C and d are two appropriately selected parameters, and $d(A, B)$ can be different distances. It is said that compared with

$A_1, A_2, \dots, A_{i-1}, A_{i+1}, \dots, A_n, B$ is the closest to A_i , and then B belongs to the A_i category [21, 22].

2.2.3. Driver's Mental Workload Recognition Method Based on Fuzzy Pattern Recognition Algorithm and Genetic Algorithm.

An algorithm model mainly uses physiological signals and vehicle speed. This research proposes a method to figure out just how much mental work drivers have, which is different from the subjective evaluation method of mental workload. According to the Pearson correlation analysis, the data (ECG, SCR, Temp, etc.) in the driver's speed and physiological signals are selected as the input parameters for the purpose of determining the mental workload. The mental workload of drivers will be evaluated and classified by adopting the Fuzzy Pattern Recognition Algorithm and Genetic Algorithm proposed in this paper. Firstly, python is applied to compress and normalize the data so that all input data parameters are between 0 and 1. The membership function set is constructed with the selected physiological signal and vehicle speed signal acting as the main input parameters of fuzzy pattern recognition. Through the genetic algorithm in MATLAB, the mean and variance in the membership function are optimized to obtain the sub-membership function, with which the prediction function for the evaluation of the driver's mental workload is constructed. The membership function set F constructed in this paper according to the driver's mental workload level is as follows:

$$F = \begin{bmatrix} f_{11}(x), f_{12}(x), f_{13}(x) \\ f_{21}(x), f_{22}(x), f_{23}(x) \\ f_{31}(x), f_{32}(x), f_{33}(x) \\ f_{41}(x), f_{42}(x), f_{43}(x) \\ f_{51}(x), f_{52}(x), f_{53}(x) \\ f_{61}(x), f_{62}(x), f_{63}(x) \end{bmatrix}. \quad (5)$$

Suppose $x_m = (x_{m1}, x_{m2}, \dots, x_{m6})$ is a set of data to be recognized by the driver. Based on the correlation analysis, 5 physiological signals and the vehicle speed will be used as input. To produce the first used Y , F is swapped into the target prediction method:

$$Y = x_m * F = \begin{bmatrix} x_{m1} \\ x_{m2} \\ x_{m3} \\ x_{m4} \\ x_{m5} \\ x_{m6} \end{bmatrix}^T * \begin{bmatrix} f_{11}(x), f_{12}(x), f_{13}(x) \\ f_{21}(x), f_{22}(x), f_{23}(x) \\ f_{31}(x), f_{32}(x), f_{33}(x) \\ f_{41}(x), f_{42}(x), f_{43}(x) \\ f_{51}(x), f_{52}(x), f_{53}(x) \\ f_{61}(x), f_{62}(x), f_{63}(x) \end{bmatrix}. \quad (6)$$

Y is a $1 * 3$ matrix, and the elements in Y are $[Y_1, Y_2, Y_3]$. According to the principle of maximum membership, if

$$y = \max(Y_i), \quad (7)$$

then, it can be determined that the data x_m to be identified belongs to Y_i .

3. Data Processing and Test Results of Driver's Mental Workload Evaluation Test

In this paper, data are collected through three sensors installed on the driver's body, with the skin conductivity and temperature sensors on the subject's left hand, as well as an ECG on the subject's chest. The Nexus4 biofeedback system connects these devices 3 to record the physiological data of the driver. Because all data sets have distinct sampling frequencies, all data is synchronized after the driving behavior applying time stamps.

3.1. Data Preparation. The hclab driving dataset public data set [23] is utilized to estimate the algorithm model suggested in this study. This study included ten individuals (3 females, 7 males) ranging in age from 23 to 57 years old ($M=35.60$, $SD=9.06$). The complete data set is 450 MB in size and consists of 2.5 million samples, including information about GPS, brightness, speed, acceleration, and physiological data. Noise should be removed and each participant's physiological features should be standardized before examining the collected data. To begin, each driver's data is compressed by taking one sample every second and choosing the average of each value. Following that, the physiological data and speed figures are standardized to a value between 0 and 1 in all driving and physiological data. In the evaluation of the driver's mental workload, five physiological values (ECG, skin conduction response (SCR) and body temperature (BTemp), HR, HRV_LF, and actual driving speed are mainly concerned. The route selected in the data is of a total length of 23.6 kilometers and consists of different types of roads. In order to evaluate the research in many aspects, 3 different types of roads are classified: 50 km/h district, expressway, and other roads (tunnels). Special types of roads are selected and added to the research, because they will trigger some special factors, such as lighting. In this sense, the type of road has a direct impact on the driver's workload. Many potential circumstances, such as many parked cars, pedestrians crossing the road, children playing nearby, or car doors suddenly opening, might cause accidents in low-speed zones due to the complexity of the environment. To ensure safety, the driver's attention must be completely focused, resulting in a higher level of mental workload when driving. Highways, on the other hand, do not necessitate as much attention due to the increased distance between vehicles. These statistics are compatible with Micheals et al.'s [24, 25] analysis; thus, the driver's mental workload level is assessed based on different road characteristics.

3.2. Construction of Prediction Function for Driver's Mental Workload. In this paper, the signals sent by the sensors on the driver are processed as data. As illustrated in Table 1, each individual stress level refers to a submembership function, with three mental workload levels corresponding to 18 submembership functions.

According to the previous introduction, 12545 sets of figures are collected as training sample data to establish a fuzzy membership function set F. The Gaussian function is chosen as the submembership function after careful thought and analysis. The following is the definition of the Gaussian function:

$$f(x) = e^{-(x-a)^2/2\sigma^2}. \quad (8)$$

Among them, a is the mean value and σ is the variance. A genetic algorithm can be used to acquire both parameters. There are 18 submembership functions in the membership function set, and 36 variables need to be optimized. The following is the membership function set F:

$$F = \begin{bmatrix} e^{-(x-a_{11})^2/2\sigma_{11}^2} & e^{-(x-a_{12})^2/2\sigma_{12}^2} & e^{-(x-a_{13})^2/2\sigma_{13}^2} \\ e^{-(x-a_{21})^2/2\sigma_{21}^2} & e^{-(x-a_{22})^2/2\sigma_{22}^2} & e^{-(x-a_{23})^2/2\sigma_{23}^2} \\ e^{-(x-a_{31})^2/2\sigma_{31}^2} & e^{-(x-a_{32})^2/2\sigma_{32}^2} & e^{-(x-a_{33})^2/2\sigma_{33}^2} \\ e^{-(x-a_{41})^2/2\sigma_{41}^2} & e^{-(x-a_{42})^2/2\sigma_{42}^2} & e^{-(x-a_{43})^2/2\sigma_{43}^2} \\ e^{-(x-a_{51})^2/2\sigma_{51}^2} & e^{-(x-a_{52})^2/2\sigma_{52}^2} & e^{-(x-a_{53})^2/2\sigma_{53}^2} \\ e^{-(x-a_{61})^2/2\sigma_{61}^2} & e^{-(x-a_{62})^2/2\sigma_{62}^2} & e^{-(x-a_{63})^2/2\sigma_{63}^2} \end{bmatrix}. \quad (9)$$

The genetic algorithm is used to optimize the mean and variance of the Gaussian function. The population type to design the genetic algorithm is a double-precision vector, and the initial populace number is 150. The mean and variance are the variables that must be optimized. The mean and variance, which indicate 36 genes in the historical approach, are the variables that need to be optimized. The range of each variable is 0.1–1.5. The lowest value is used to optimize the fitness function. As a result, the fitness function is chosen as the inverse of the recognition accuracy of the driver's mental effort, which is described as follows:

$$\text{Fitness Function} = 1 / \left(\sum_{i=1}^n \left(\frac{\text{right_}L_i}{\text{total_}L_i} \right) + \sum_{i=1}^n \left(\frac{\text{right_}H_i}{\text{total_}H_i} \right) + \sum_{i=1}^n \left(\frac{\text{right_}X_i}{\text{total_}X_i} \right) \right). \quad (10)$$

In the formula, $\text{right_}L_i$ refers to the low-level mental workload of the i th correctly identified driver, $\text{right_}H_i$ the high-level mental workload of the driver, and $\text{right_}X_i$ the middle-level mental workload of the driver. The objective functions are optimized according to the minimum value because the genetic algorithm is implemented using MATLAB software. The fitness function is set to be the reciprocal of the overall state accuracy rate. Individuals are genetically selected based on their fitness function. Selection, crossover, and mutation are the most basic actions in evolutionary algorithms. With the crossover probability set to 0.8, the mutations probability set to 0.2, and the genetic algebra set to 50 generations, the single-point crossover method is chosen as the selection algorithm. The genetic algorithm will be completed when the evolutionary algorithm achieves the algebra of heredity or when the fitness value of the parameter individual gets the optimal outcome.

3.3. Analysis of Experimental Data and Test Results. In this paper, in order to clean the drivers' data, the data is firstly detected for abnormal compression, and the box diagram in python is used to detect the abnormal signal of the drivers. In Figure 1, the abnormal data detection of the driver's actual

TABLE 1: Correspondence of submembership function.

	Low mental workload	High mental workload	Medium mental workload
Speed	$f_{11}(x)$	$f_{12}(x)$	$f_{13}(x)$
ECG	$f_{21}(x)$	$f_{22}(x)$	$f_{23}(x)$
SCR	$f_{31}(x)$	$f_{32}(x)$	$f_{33}(x)$
Temp	$f_{41}(x)$	$f_{42}(x)$	$f_{43}(x)$
HR	$f_{51}(x)$	$f_{52}(x)$	$f_{53}(x)$
HRV_LF	$f_{61}(x)$	$f_{62}(x)$	$f_{63}(x)$

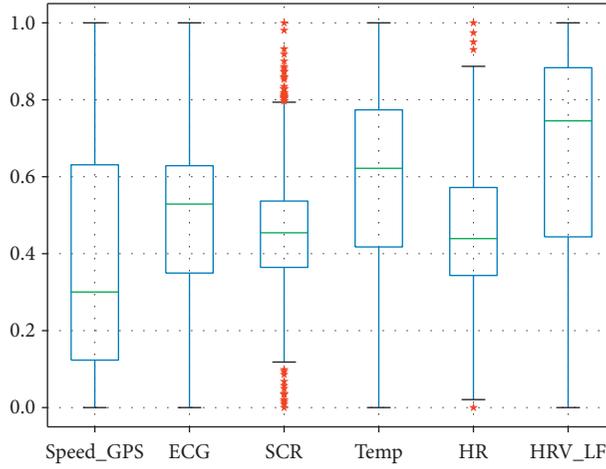


FIGURE 1: Detection of abnormal data in the collected characteristic signal of the driver.

speed signal and the physiological signal is displayed. Among them, the driver's SCR and HR signal abnormal data are relatively large. Since the amount of data is large enough, the abnormal value is not processed.

Then, the physiological data of 10 drivers and the actual driving speed on different types of roads are analyzed by the Pearson correlation coefficient method for correlation and significance analysis. One driver's mental workload level has a negative correlation with ECG ($r = -0.311288$, $p = 4.25996e - 42 < 0.001$), has a strong correlation with SCR ($r = -0.532609$, $p = 1.35424e - 133 < 0.001$), has a negative correlation with Temp ($r = -0.375079$, $p = 9.40519e - 62 < 0.001$), and has a small negative correlation with HR ($r = -0.09167$, $p = 9.23865e - 05 < 0.001$) and HRV_LF ($r = -0.09501$, $p = 5.01035e - 05 < 0.001$). Another driver's mental workload level has a negative correlation with ECG ($r = -0.456788$, $p = 2.75777e - 88 < 0.001$), has a negative correlation with SCR ($r = -0.239412$, $p = 1.46432e - 23 < 0.001$), has a positive correlation with Temp ($r = 0.535968$, $p = 6.949392e - 127 < 0.001$), has a positive correlation with HR ($r = 0.60658$, $p = 3.521708e - 171 < 0.001$), and has a positive correlation with

HRV_LF ($r = 0.154152$, $p = 1.706706e - 10 < 0.001$). There is also a driver whose mental workload level is positively correlated with HRV_LF ($r = 0.45865$, $p = 5.22273e - 90 < 0.001$). Through the correlation analysis of all drivers, the results show that there is a significant impact, and the correlation presents different trends for different drivers. Therefore, 5 kinds of physiological signals will be adopted in this paper as the input of mental workload classification combined with the speed of the self-vehicle. The genetic algorithm optimizes the mean and variance of the Gaussian function, which is shown in Figure 2. Figure 3 displays the entire process of genetic algorithm training. It can be seen from the change in the fitness value that after about 30 generations, the fitness value of the population has stabilized, and the best fitness value is 0.402845.

In the three levels of mental workload tested, 4/5 of the total number of samples are used as the training samples of the algorithm, and the remaining 3768 sample data are used as the test samples to verify the algorithm proposed in this paper. In the verification data, a set of data is randomly selected:

$$\begin{aligned}
 x_1 &= [0.0114521190.5792079960.1603786620.0600103680.2183348220.725127844], \\
 x_2 &= [0.9565033970.6134108040.2677305720.3302591850.369380980.11622374], \\
 x_3 &= [0.5191294170.7137337520.2701364330.1530492250.4776704530.441266565].
 \end{aligned} \tag{11}$$

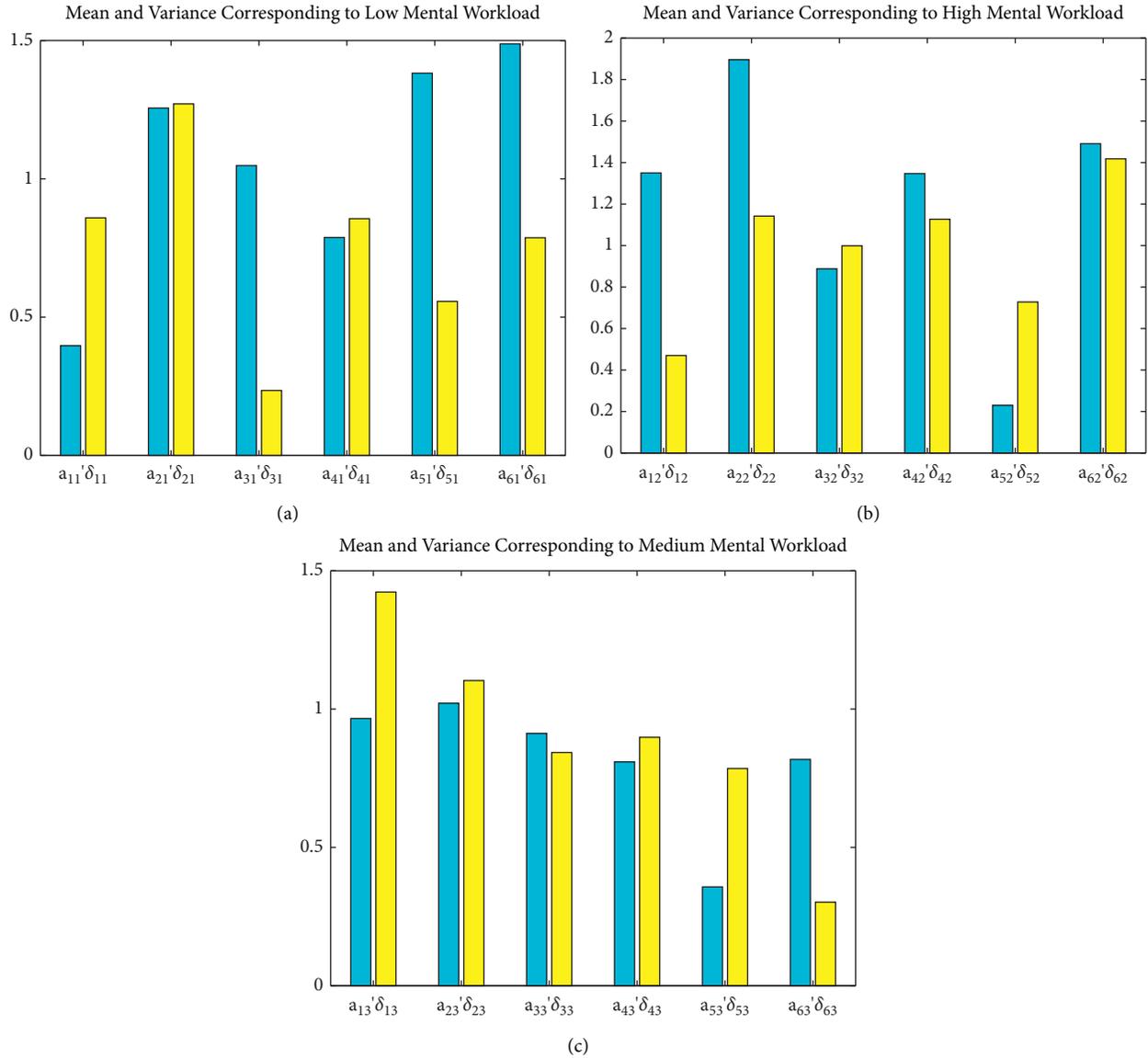


FIGURE 2: The corresponding mean and variance of each mental level optimized by the genetic algorithm.

Here, x_1 is the verification data for low mental workload, x_2 is the verification data for high mental workload, and x_3 is the verification data for the middle mental workload. Assuming that the above classification is not known, and the data of the above 3 states are substituted into the target prediction function, it can be inferred that $Y_1 = (1.6411 \ 1.30931.4839)$, $Y_2 = (1.5818 \ 2.1004 \ 1.9576)$, and $Y_3 = (1.9305 \ 1.9001 \ 1.9645)$. Substituting the three known types of data of $x_1, x_2,$ and $x_3,$ the data is analyzed using the fuzzy pattern matching principle of maximal membership into the target prediction function. Because 1.4338 is the largest of the three Y_1 data, it is considered to have a low amount of mental burden, suggesting that the identification result is correct. Among the three data of $Y_2,$ 2.0204 is the largest, so it is judged as a high level of mental workload, which indicates that the recognition result is correct. Among the three data of $Y_3,$ 2.7567 is the largest, so it is judged as a medium level of mental workload, which indicates that the recognition result is correct.

In this paper, a total of 5405 sample data of 10 drivers are used as test samples. In the Fuzzy Pattern Recognition Algorithm suggested in this paper, the target prediction function is incorporated into the target prediction function. Among them, the recognition accuracy of the low level of mental workload is 99.71%, and the recognition accuracy rate of the high level of mental workload is 93.94%. Due to the small sample size and limited environmental factors, the medium level of mental workload was mistakenly assessed as a low level of mental workload, so in-depth research can be specifically targeted at the medium level of mental workload in the later period. In this paper, the driver's low level of mental workload and high level of mental workload are successfully and accurately identified, and the experimental results are analyzed with the ROC curve. The receiver operating curve is the full name of the ROC curve. It is a curve with the true positive rate on the coordinate and the false positive rate on the abscissa, based on a series of different two classification methods (cutoff value or decision threshold).

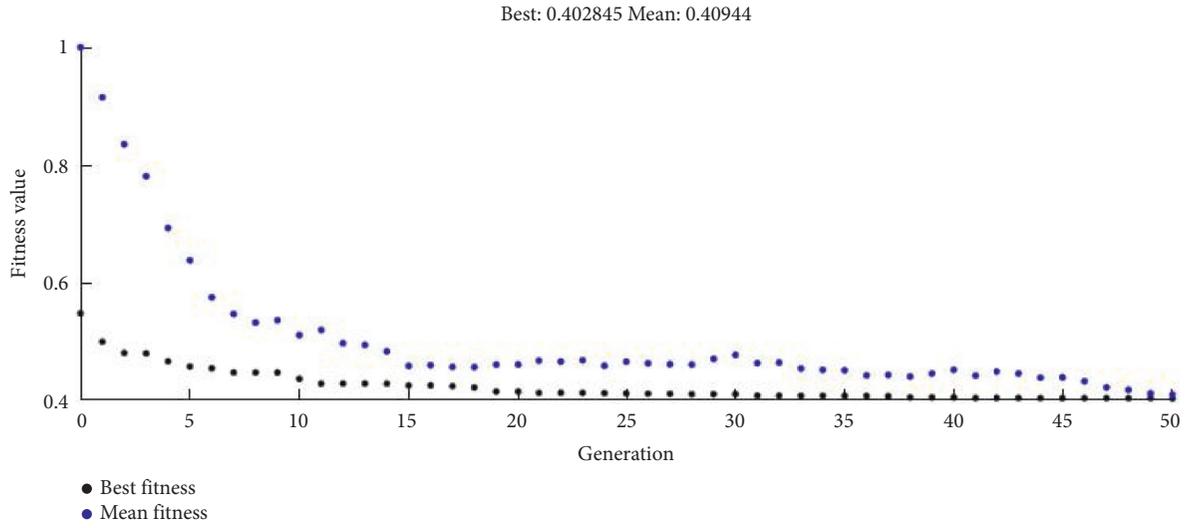


FIGURE 3: The genetic process of the fitness function value.

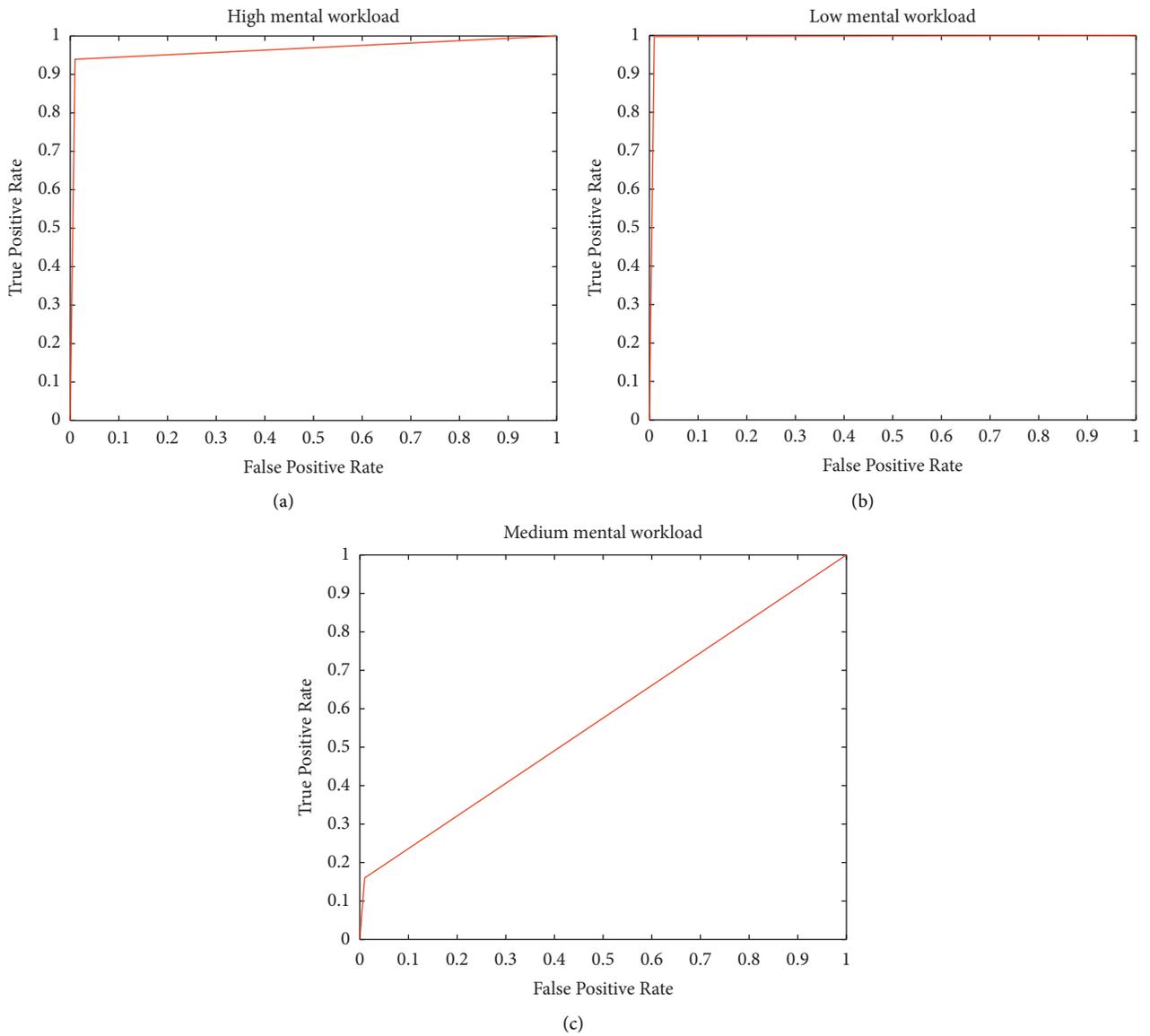


FIGURE 4: ROC curve graph of fuzzy pattern recognition algorithm for evaluating mental workload.

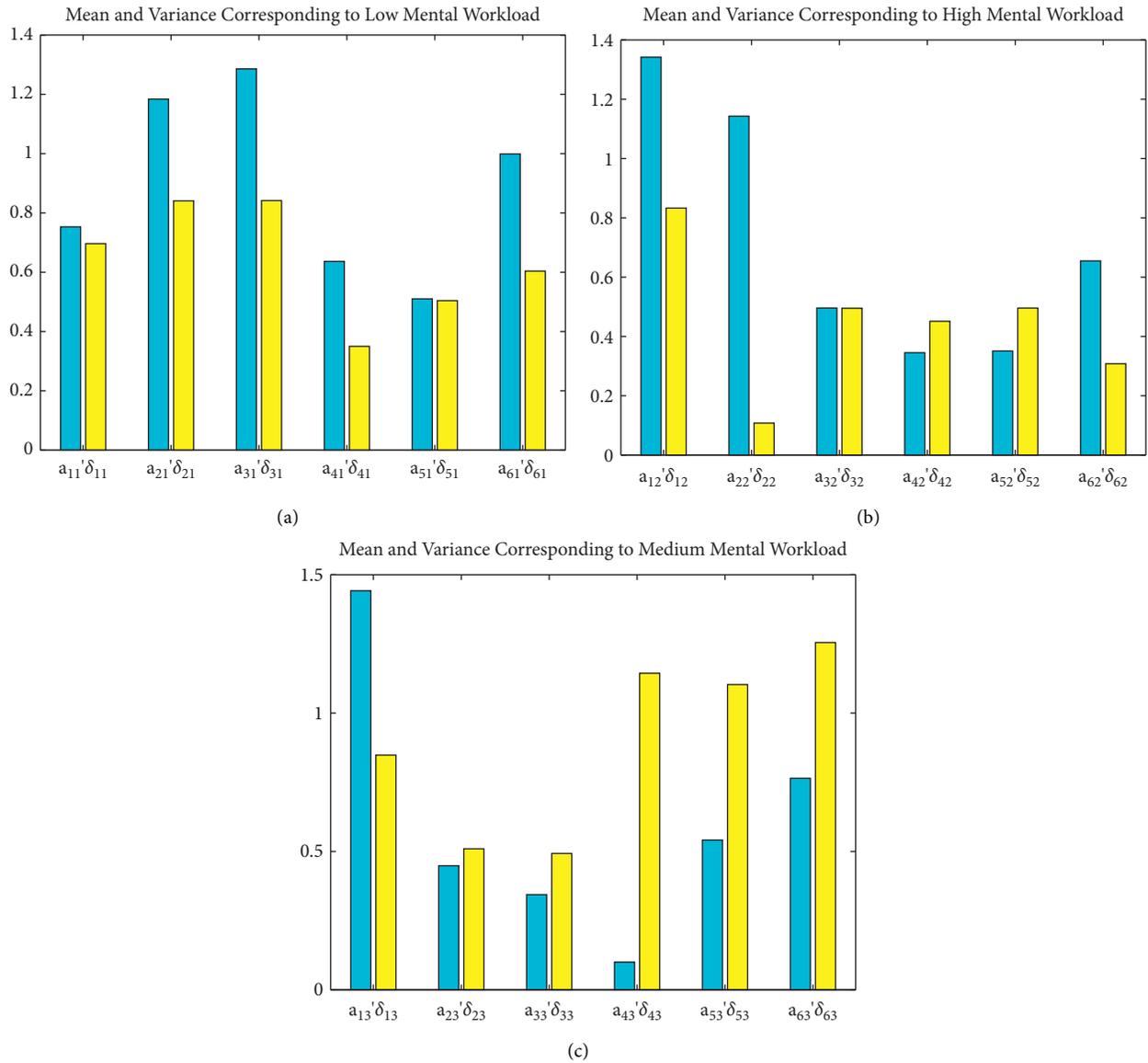


FIGURE 5: The corresponding mean and variance of each mental level optimized by a simulated annealing algorithm.

Because the ROC curve is closer to the upper left corner, the method is more accurate. Figure 4 depicts the ROC curve for pattern recognition of the driver’s mental load level using fuzzy pattern detection algorithms. The categorization effect has achieved its target.

3.4. Algorithm Comparison. This section compares the algorithm suggested in this work to other algorithms. First, the simulated annealing technique chosen as the optimization function is compared to the genetic algorithm optimization proposed in this research. The resultant mean and variance distribution is displayed in Figures 5 and 6 and is inserted into the fuzzy pattern recognition method for the identification of drivers’ mental workload when the simulated annealing algorithm is used to optimize the callous and variance of the Gaussian purpose. The identification accuracy rate for a low type of cognitive workload is 81.61 percent, while the

recognition accuracy rate for a high level of mental strain is 81.61 percent of mental workload which is 100%. Due to the small number of samples, all medium levels of mental workload were misidentified as high levels of mental workload. It can be seen that the recognition accuracy of the genetic algorithm proposed in this paper for optimization is higher than that of the Simulated Annealing Algorithm.

Second, this paper’s method is compared to WEKA’s J48 algorithm, which is a decision tree algorithm. In order to evaluate the risk of the project and practicability, a decision tree is a decision assessment method to calculate the possibility that the estimation of the net present is greater than or equal to zero by having to build a tree structure based on the known frequency of occurring of various scenarios. It is a graphical representation of how to use probability analysis simply. As a result, it is known as a decision tree, because this type of decision branch is drawn into a graph in the same way as that of tree branches. Logistic regression is a

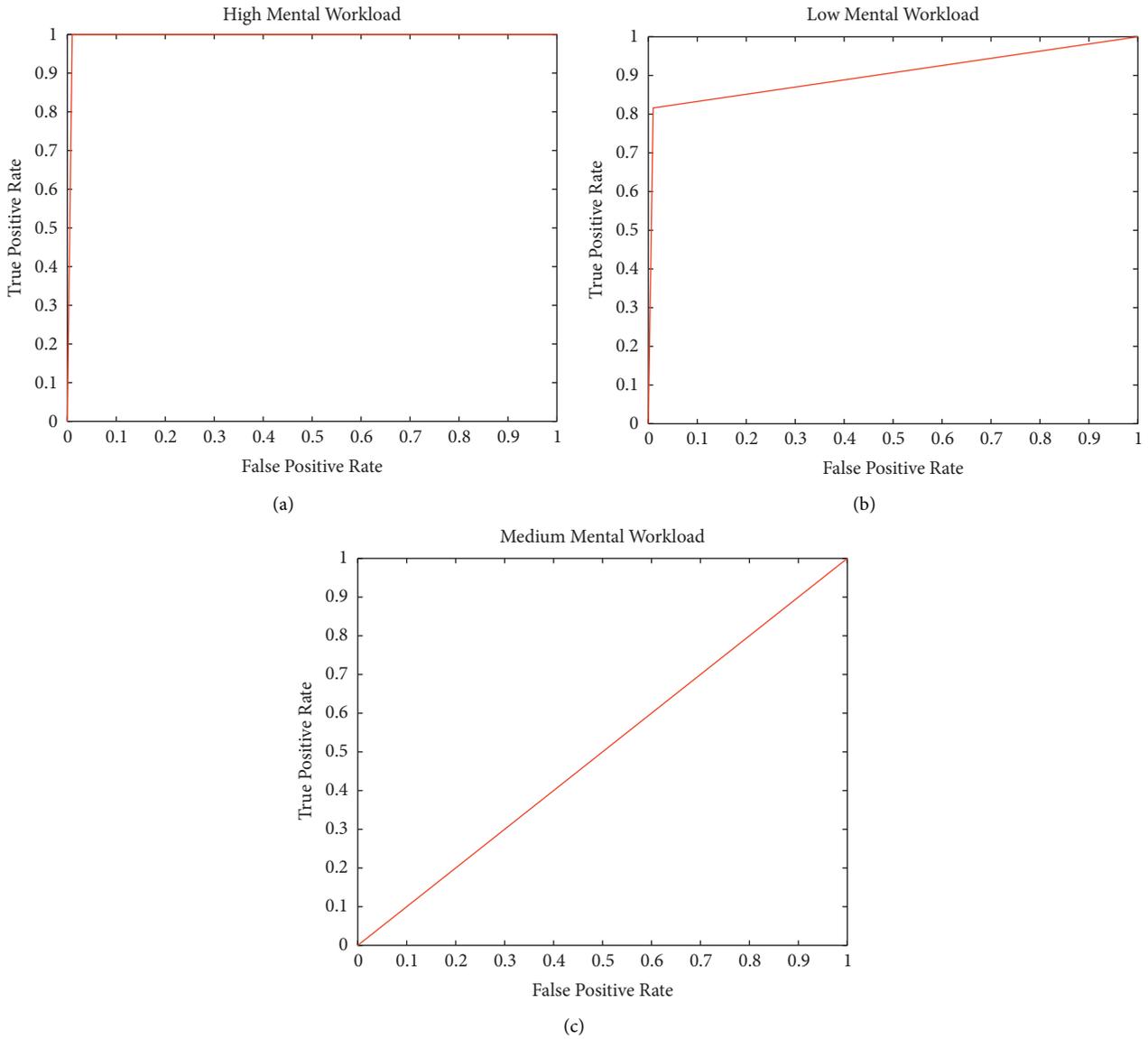


FIGURE 6: ROC curve graph of simulated annealing algorithm for evaluating mental workload.

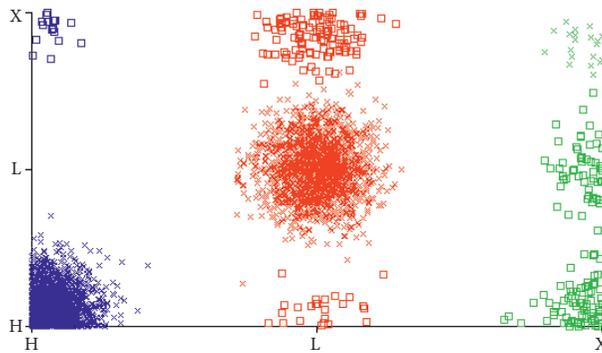


FIGURE 7: Misclassification of J48 algorithm for mental workload level.

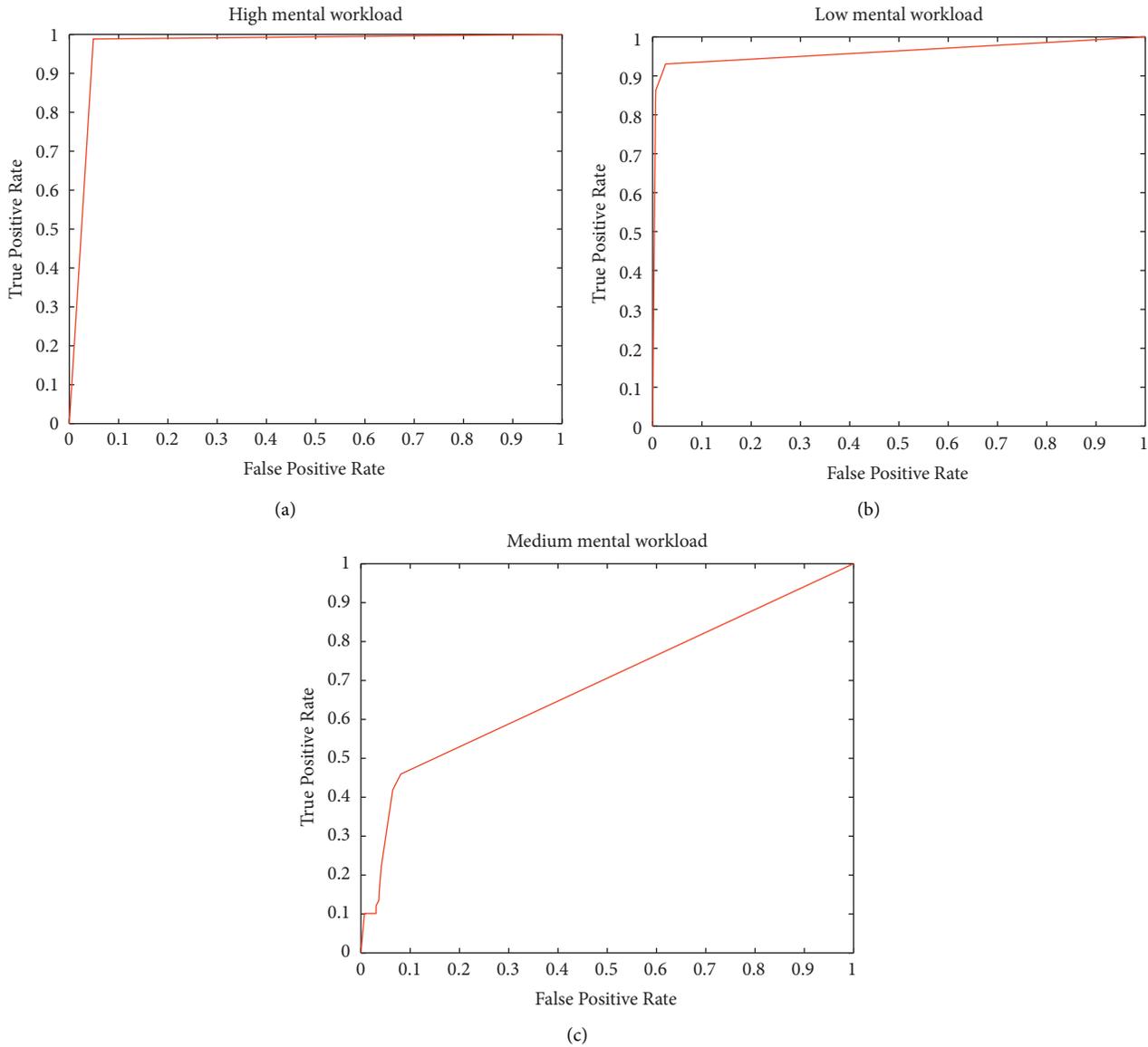


FIGURE 8: ROC curve graph of J48 algorithm for evaluating mental workload.

probabilistic classifier in machine learning that depicts a mapping link between objects and object outcomes. The algorithm is chosen to perform classification prediction analysis on the data in this work, with 3484 properly classified instances, a Kappa of 0.8594, and a visual classification error of Figure 7. The box indicates correct classification, and \times indicates incorrect classification. The ROC curves of the three levels of mental workload of the driver are shown in Figure 8. The combination of fuzzy image recognition algorithm and genetic algorithm chosen in this study is much superior to other methods for forecasting the driver’s mental workload, according to comparative analysis.

4. Conclusions

The application of existing onboard information systems and the complexity of road traffic control information increase the mental workload of drivers, which indicates that

the driver’s mental workload assessment is the key problem to be solved. The mental workload of drivers is properly recognized in this research, laying the groundwork for the integrated and optimum design of automatic driving assistance systems and traffic information. The following innovative theories and methods are proposed: in terms of the identification of the driver’s mental load.

- (a) The physiological signal is combined with the vehicle signal, and the input indicators for the driver’s mental load level are obtained according to the correlation and significance level
- (b) To determine the driver’s mental burden, a model based on fuzzy pattern recognition and a genetic algorithm is built. In order to analyze the influence mechanism of physiological signals and self-vehicle speed on the driver’s mental load, the correlation coefficient and significance level were obtained by

analyzing the correlation between physiological data and road types. Subsequently, the data is pre-processed, and the characteristic indexes for mental workload recognition are selected. The level of a driver's mental effort is classified using a fuzzy pattern recognition algorithm. It is also compared to the J48 Classification Algorithm and the Simulated Annealing Optimization Algorithm. The test results demonstrate that the accuracy of the algorithm model proposed in this paper for identifying the level of mental workload is better than other algorithms, which provides new theoretical support for evaluating the mental workload level of L3+ drivers

Due to the quantity limitation of collected sample on driver's mental workload, there are still some shortcomings:

- (a) A general methodology for calculating the mental effort of drivers is proposed. To get more precise findings, a better way is to create a perfect model for each level of mental workload
- (b) The parameters for classifying the driver's mental workload level should be investigated further. The accuracy of the medium mental exertion level is also high. In future research, the main research direction will be to classify the level of driver's mental workload according to specific standards and to carry out the L3+-based driver's mental workload evaluation test in the case of nondriving tasks under the main driving task

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors would like to declare that they have no conflicts of interest.

Acknowledgments

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