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Modeling and Recognition of Driving Fatigue State Based on R-R Intervals of ECG Data

LINHONG WANG[1], JINGWEI LI[2], AND YUNHAO WANG[3]
[1]School of Transportation, Jilin University, Changchun 130022, China
[2]Department of Electronic Engineer, Stony Brook University, Stony Brook, NY 11790, USA
[3]School of Mathematics and Statistics, Northeast Normal University, Changchun 130024, China

Corresponding author: Yunhao Wang (wangyh533@foxmail.com)

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ABSTRACT Driving fatigue is an important contributing factor to traffic crashes. Developing a system that monitors the driver's fatigue level in real time and produces alarm signals when necessary, is important for the prevention of accidents. In the past decades, many recognition algorithms were developed based on multiple indicators. However, the relationship between R-R intervals of ECG and driving fatigue has not been studied. We develop a model to recognize the driving fatigue state based on R-R intervals. The cluster effect in the R-R interval sequence is found based on the stationary test and ARCH effect test. Then the AR (1)-GARCH (1, 1) model is developed to fit the time sequence of R-R intervals. The conditional variance of the residual R-R sequence is used to recognize whether there are changes in driving states. Field data was collected on the freeway between Baicheng and Changchun cities, where 10 drivers took part in the experiments. Validations are conducted to test the effectiveness of the developed model, and the results show that the recognitions of driving fatigue for the 10 drivers are correct in all cases. In addition, the recognition time delay is smaller than 5 minutes.

INDEX TERMS Driving fatigue, recognition model, R-R intervals, conditional variance.

I. INTRODUCTION

A. BACKGROUND

Driving fatigue is an important contributing factor to traffic safety. Some studies have demonstrated that the driver fatigue accounts for 16% of all traffic crashes and over 20% of crashes on highways [1], [2]. Therefore, the driver fatigue recognition remains to be a big challenge to meet the demands of future intelligent transportation systems. Developing a system that monitors the driver's state in real time and produces alarm signals when necessary, is important for the prevention of accidents [3]–[5].

Fatigue is a complex state which manifests itself in the form of the lack of alertness and reduced mental or physical performance, often accompanied by drowsiness [6]. It is a serious problem, which is believed to be a major cause of fatal road accidents. In recent years, many studies were conducted on the topic of driving fatigue recognition. One of the key steps towards developing a fatigue recognition algorithm is the selection of indicators to be used [7]–[9]. Current algorithms can be classified into three categories according to the indicators used.

The first category is the driver's behavior based method. Here the video monitoring technique is employed to obtain the parameters of the driver's head and eyes movements as well as body posture. Different algorithms are developed that use these parameters to judge whether the driver is in the fatigue state. The blink duration, blink frequency, partial eye closures, eye closures, saccade frequency, and large head and body movements are the six most important parameters [10], [11].

The second category is the vehicle operational performance based method. When a driver is in the fatigue state, the time spent on perception and decision increases, which contributes to the deterioration in the operational performance (such as the reaction time, lane position deviation, and hand movements to control the steering wheel). Small changes in these factors can be used to calibrate and predict the driver's fatigue [12], [13].

The third category is the physiological indexes based method. There is considerable research to detect fatigue based on several measurements. Most of them involve the

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Electroencephalogram (EEG) and Electrocardiogram (ECG). A number of studies on the EEG show that the α wave, β wave, δ wave and θ wave are closely related to the driver's state [15]–[18].

Amongst a number of indicators that can be used for fatigue detection, the ECG is considered to be a significant and reliable signal. Some studies on the ECG show that it is closely associated with mental and physical activities. For different activities ECG recording may differ in the terms of either magnitude or frequency or both [19], [20].

Some researchers studied the relationship between single or multiple ECG indicators and driving fatigue. These studies can be roughly divided into two groups. The first group obtains the time or frequency domain parameters of a single ECG indicator first, and then analyzes the relationship between the ECG indicator and driving fatigue from the view of traditional statistical approaches. For example, Patel *et al.* [21] present an artificial intelligence based system which can detect early onset of fatigue using the heart rate variability (HRV) as a physiological measure. The detection performance is tested using a set of electrocardiogram (ECG) data recorded under laboratory conditions. The accuracy of the neural network is shown to be 90%. Jung *et al.* [22] design an embedded ECG sensor with electrically conductive fabric electrodes on the steering wheel of a car to monitor the driver's health conditions. Practical tests are conducted using an embedded ECG sensor with a wireless sensor node, and the performance was assessed using a non-stop 2h driving test. The driver's health conditions such as the normal, fatigue and drowsy states are analyzed by evaluating the HRV in the time and frequency domains. Wang *et al.* [23] develop a model of the relationship between the HRV and driving time based on the Gaussian model using field collected data. The level of sensitivity of the MHR to the driving time is studied, and the results show that the driving time is positively correlated with the MHR, where with an increase in the driving time the MHR increases as well, implying that the active fatigue level of the driver becomes worse.

The second group recognizes the driving fatigue level based on multiple ECG indicators. Yang *et al.* [3] propose a driver fatigue recognition model based on the dynamic Bayesian network. Both ECG and EEG signals are included in the model. The experimental validation shows that the ECG and EEG are significant factors for inferring the fatigue state of a driver. Zhao *et al.* [24] use the approximated entropy of the ECG, and the lower and upper bands of the power of the HRV to assess mental fatigue in a driving simulator. The experiments reveal that these indicators are significantly different before and after finishing the driving task.

B. OBJECTIVES AND CONTRIBUTIONS

Based on the above statements we can see that most indicators of the ECG signal used in existing literatures are the MHR and HRV. The R-R interval is the time elapsing between two consecutive R waves in the ECG and it is one of the most important indicators of the ECG signal, but there are few studies focusing on the relationship between this indicator and driving fatigue.

Generally, the ECG signal is relatively stable when a driver performs a driving task in the alert state. In such a condition, external stimuli to the driver do not produce significant changes in the ECG signal, such as the MHR, HRV, and the time series of the R-R intervals. However, when the driver is in the fatigue or drowsiness state, the capability to deal with traffic conflicts is deteriorated because of the reduced mental alertness. Therefore, weak external stimuli to the driver result in large fluctuations in the ECG signal. From the analysis it can be found that the ECG data is stable on the whole but fluctuates in parts. This feature can be well expressed by the time series model AR (1)-GARCH (1, 1) borrowed from the financial field. Therefore, in this paper we try to use this model to analyze the relationship between R-R intervals and driving states, and then develop a driving fatigue recognition model. This is the main motivation of our paper.

From the medical point of view, the heart motion is an information changing process, and each heart beat uses a part of the information of the previous beat. The time series of R-R intervals contains some useful information about heart beats, which can indicate instantaneously small fluctuations in the continuous heart beat. In addition, driving fatigue is a cumulative process, namely, the driver cannot fall into the fatigue state unexpectedly. This is the reason why we choose the R-R interval as the indicator.

The contributions of this study are threefold. First, a driving fatigue state recognition algorithm is developed based on the fluctuation characteristics of the cluster effect, which can be obtained from the conditional variance of the residual R-R interval sequence. In this algorithm, there is no need to set threshold values for recognition indexes, which overcomes the limitations of previous studies that divided the driving state into several levels according to the driver's subjective feelings. Second, the AR (1)-GARCH (1, 1) model is introduced to analyze R-R time series data, and a reliable recognition model is developed. Third, field data is collected on a freeway to test the algorithm, and the R-R interval is proved to be an excellent indicator to recognize driving fatigue; this is the most valuable result of this study.

The rest of this paper is organized as follows. The next section presents the field experiment plan and preliminary data analysis of R-R intervals. In Section III, a recognition algorithm for driving fatigue based on R-R intervals is developed. In Section IV, the algorithm is tested using field data on multiple drivers. The conclusion in the last section summarizes the findings of this paper and presents future work.

II. FIELD EXPERIMENTS

A. EXPERIMENT DESIGN

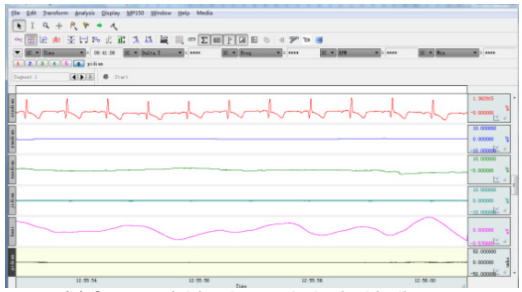
Real vehicle experiments were conducted on the G302 freeway (Changchun-Baicheng) to collect required drivers' psychological data. The G302 freeway is a high-grade highway

(a) Roadside landscape with villages

(b) Roadside landscape in the plain

FIGURE 1. Roadside landscapes of G302 freeway (Changchun-Baicheng).

(a) Equipments in the field experiments



(b) Curves of driver's psychological indicators

FIGURE 2. Equipments in the experiments and curves of psychological indicators.

in Jilin Province, China, with two lanes in each direction. It connects Changchun City and Baicheng City, and is about 345 km long. This freeway passes through a plain and the roadside landscape is composed of farmlands, villages and trees. Therefore, the monotonous landscape makes drivers fall into the fatigue state easily, which is suitable for the collection of required data. Figure 1 shows typical landscapes of the G302 freeway.

The experiments were conducted for 10 days, and 10 drivers from 25 to 45 years old were employed to perform the experiments. The average age of the 10 drivers is 32.6. 5 drivers are taxi drivers, 2 drivers are Ph.D. students and 3 drivers are government staff. None of them has traffic accident record. The drivers were required to have sufficient sleep before each experiment. They were not allowed to drink wine or coffee, or take any medicine, to avoid any impact on psychological indicators. The MP100, a 16 channels poly-physiograph, was used to record the physiological indicators of the drivers. Each driver performed each experiment at some time between 8:00 and 18:00. During the experiments, all investigators in vehicles were silent. The drivers were able to arrange for some rest time when feeling tired, to ensure safety. The investigators in vehicles asked the driver about the fatigue level every 15 minutes and recorded it. In addition, markers were set in the Biopac recording software to help the subsequent data analysis in the lab. The equipment used in the experiments and psychological indicator curves are shown in Figure 2.

In the experiments the drivers' fatigue states are divided into four levels, which are the alert, slight fatigue, serious fatigue and drowsiness states. The famous Pearson-Byars fatigue scoring method classifies fatigue into 13 levels. It can exactly quantify the driver's fatigue state. However, in our study the drivers' real fatigue states were asked by investigators during driving. If the fatigue states were divided into many levels, the drivers would spend much time on judging which fatigue level is best to describe the current state. This would have impact on the mental state and driving safety.

Accordingly, to let the drivers judge their real states easily and exactly while driving, only four fatigue levels were employed in this study. The four states are represented by 1, 2, 3 and 4, respectively, which made possible for the drivers to answer quickly. In the state of alertness, the drivers exhibit quick reaction to external stimuli and strong operation of the vehicle. After having driven for a period of time, the driver begins to feel slight fatigue because of the physical and mental workload. The serious fatigue state occurs after the driver has driven for a long time. In such a condition, the driver is in a severely tired state, and his reaction and operation abilities decrease quickly. In the state of drowsiness, the driver falls into sleep occasionally, while not being able to control the vehicle well. Thus, a rest in a service area is needed.

B. DATA ANALYSIS

The data analysis module of the Biopac software was used to extract the R-R intervals of the drivers' ECG data. Then, the time series analysis was conducted on the R-R intervals. Some R-R intervals of the ECG are shown in Table 1.

Generally, a time series with random fluctuations is composed of two parts, the first part being a time series with

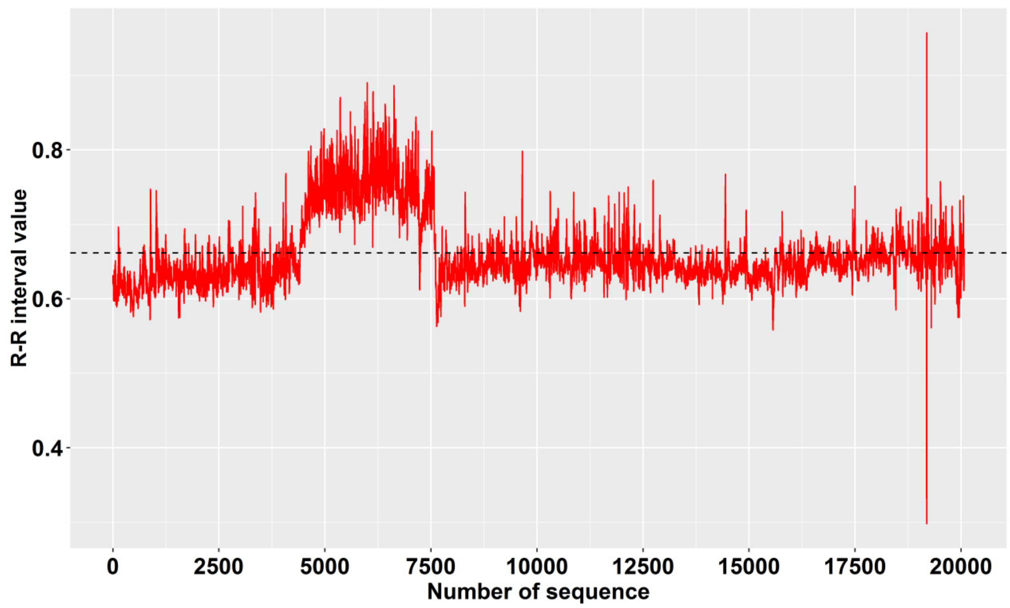


FIGURE 3. The R-R interval sequence obtained from field data.

TABLE 1. Part of the R-R intervals of ECG samples.

NO.	R-R intervals	NO.	R-R intervals
1	0.68	16	0.691
2	0.676	17	0.684
3	0.672	18	0.679
4	0.676	19	0.68
5	0.68	20	0.681
6	0.684	21	0.678
7	0.683	22	0.676
8	0.683	23	0.676
9	0.685	24	0.679
10	0.693	25	0.682
11	0.694	26	0.684
12	0.693	27	0.683
13	0.689	28	0.678
14	0.69	29	0.676
15	0.691	30	0.676

deterministic information and the second part being random fluctuations around the deterministic information. The random fluctuations can also build a time series, which is called the structural residual series, or simply residual series.

The fluctuations of the residual series are usually employed to describe the cluster effect of the time series. The cluster effect is defined as follows: after eliminating the impact of certain deterministic non-stationary factors, the residual series is stationary most of the time. However, the volatility of the residual series is continuously small or large in some periods. Thus, if the time sequence has the volatility cluster effect, its residual series has to meet two conditions: (i) be stable on the whole; (ii) has continuous volatility in some parts.

Taking the R-R time series shown in Figure 3 as an example, the deterministic information is that the R-R time series fluctuates around a fixed value (about 0.66) while there are large volatility at some special time points (e.g. 19190).

However, whether there is the cluster effect in the R-R intervals depends on the results of statistical tests, such as the stationary test and autoregressive conditional heteroskedasticity (ARCH) effect test. Figure 3 can only provide preliminary judgment. First, the stationary test should be implemented for the original sequence, or rather residual sequence (original sequence minus its mean at every point). If the test shows that the residual sequence is stationary, we can conclude that most of the time the sequence fluctuates around the fixed value. Then, the ARCH effect test for the residual sequence is conducted to test whether there are significant fluctuations in the residual sequence at some time points. The ARCH test is a special heteroscedastic test, which requires the heteroscedasticity of the sequence and the heteroscedasticity produced by certain autocorrelations. The autocorrelations can be fitted using the autoregressive model on the residual sequences. If the residual sequence passes the ARCH test, we can conclude that there is cluster effect in it.

1) STATIONARY ANALYSIS OF THE RESIDUAL SEQUENCE BASED ON THE UNIT ROOT TEST

Since the human's heart rate is constant, the model of the R-R interval sequence can be set as follows:

$$x_t = c + u_t \tag{1}$$

TABLE 2. Results of the stationary test for driver 1 based on the residual R-R sequence data.

Test method	Statistic	P-value	5% significant level
ADF Test	T=-6.604	0.000	Unit root hypothesis is rejected
PP Test	T=-23.474	0.000	Unit root hypothesis is rejected
DF-GLS Test	T=-4.707	(5% critical) value=-1.941	Unit root hypothesis is rejected
ERS Test	P=0.581	(5% critical) value=3.260	Unit root hypothesis is rejected
NP Test	All statistics are smaller than 5% critical value		Unit root hypothesis is rejected

Note: ADF: Augmented Dickey–Fuller test; PP: Phillips-Person test; DF-GLS: Dickey-Fuller Generalized Least Square test.

TABLE 3. Autocorrelation coefficient of each order of residual sequence.

Order	Autocorrelation	Partial Correlation	Q-statistic	P-value
1	0.981	0.981	19326	<0.001
2	0.956	-0.183	37666	<0.001
3	0.929	-0.025	54988	<0.001
4	0.907	0.149	71525	<0.001
5	0.888	-0.025	87345	<0.001
6	0.868	-0.013	102484	<0.001
7	0.847	-0.038	116895	<0.001
8	0.826	-0.016	130609	<0.001
9	0.809	0.092	143760	<0.001
10	0.798	0.123	156567	<0.001
11	0.794	0.123	169240	<0.001
12	0.794	0.069	181899	<0.001

where x_t denotes the R-R interval sequence of a driver; t is the sequence number of the collected R-R interval data; c is the average data of the R-R interval sequence data; and u_t represents the residual sequence of R-R intervals.

The R-R interval data of driver 1 is taken as an example here to explain the model and the stationary test. The model is listed below.

$$x_t = 0.6615 + u_t \tag{2a}$$
$$u_t = x_t - 0.6615 \tag{2b}$$

The key point in (2) is series $\{u_t\}$. In the economics field, the unit root test is usually employed in the stationary analysis of residual time series. The test methods include the ADF test, PP test, DF-GLS test, ERS test, and NP test. The null hypothesis in these tests is that the residual sequence has a unit root and is not stationary. The results of the unit root tests based on the data on driver 1 collected from the field experiments are shown in Table 2.

Under the 5% significant level, the unit root hypothesis is rejected by the five test methods. Thus, the residual sequence of R-R intervals $\{u_t\}$ for driver 1 can be deemed stationary.

2) ARCH EFFECT TEST FOR THE RESIDUAL R-R INTERVAL SEQUENCE BASED ON THE Q STATISTICAL METHOD

The homogeneity test of variance can be converted to the autocorrelation test of the residual square sequence. Therefore, the Q statistical method is used to test the autocorrelation of the residual square sequence, to simply find whether there is the ARCH effect in the residual sequence. The null hypothesis of the Q method is that the variance of the residual square sequence is homogeneous. The autocorrelation coefficients of each order are tested using the Eviews software, and the results are shown in Table 3.

In Table 3 we pay more attention to the third column and the last column. The third column displays the partial correlation, which offers the net effect from the t-th R-R interval to the $(t\text{-}s)$-th, i.e., eliminates the effect from 1-st, 2-nd, …, $(s-1)$-th to the t-th R-R interval and analysis the effect between the t-th R-R interval and the $(t-s)$-th, where s is the first columns "Order" in the table. Therefore, the t-th R-R interval mainly effects by $(t-1)$-th, with the partial correlation 0.981. In the last rows, all P-values are significantly smaller than 0.05 (actually smaller than 0.001), which indicates that the residual sequence has autocorrelation in each order, thus there might be the ARCH effect.

Overall, the residual R-R interval sequence of driver 1 passes the stationary test and the ARCH effect test, which demonstrates that there is the volatility clustering in the residual R-R interval sequence. The stationary test and ARCH effect test are also conducted for the R-R interval data of the other 9 drivers, and the same conclusion is obtained. Therefore, it can be concluded that the R-R interval sequences of all drivers have the cluster effect.

III. DEVELOPMENT OF FATIGUE RECOGNITION MODEL

In this section, the AR-GARCH model is developed to describe the R-R time series. Then, a recognition model for driving fatigue is proposed. The procedure of developing the recognition model includes the following four steps.

Step 1: Development of the AR-GARCH model.

Step 2: Development of the AR (1)-GARCH (1, 1) model.

Step 3: The ARCH effect test of the AR (1)-GARCH (1, 1) model.

Step 4: Recognition of the driving fatigue state.

A. AR-GARCH MODEL

1) THE GARCH MODEL

If a time series passes the stationary test and ARCH effect test, the ARCH model should be considered first to fit the data. In fact, the ARCH model takes into account the historical fluctuation information, and the auto regression form is used to describe the changes caused by fluctuations [25]. For a time series, the historical information and corresponding conditional variance change with time. The conditional variance, which can reflect the real-time fluctuations of the sequence, can be well described by the ARCH model. The ARCH model has the following structure:

$$\begin{cases} x_t = f(t, x_{t-1}, x_{t-2}, \cdots) + u_t \\ u_t = z_t\sqrt{h_t} \\ h_t = w + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 \end{cases} \tag{3}$$

where $f(t, x_{t-1}, x_{t-2}, \cdots)$ represents the determinacy information set of $\{x_t\}$ at time point t; t is the number of time points; u_t is the residual sequence; z_t is the normalized residual sequence which follows the standard normal distribution N(0, 1); h_t is the conditional variance of the residual sequence; λ_j and w are parameters; and q denotes the moving average order.

However, in reality, the conditional variance functions (CVF) of some residual time series have the feature of auto regression. Taking the R-R interval sequence as an example, the heteroscedasticity function (or the CVF) has long-term memory because of the physiological characteristics of human. The fluctuation level of the R-R interval sequence at one time point is affected by previous fluctuations. Namely, the current conditional variance is affected by the previous conditional variance values. The ARCH model is only suitable for time series with short-term auto regression process, and not suitable for the R-R interval sequence with long-term auto regression process. Therefore, a generalized ARCH model, the GARCH model developed by Engle and Bollerslov, is proposed to model the residual R-R interval sequence. The GARCH takes the p-order auto regression process of the CVF based on the ARCH model, and is suitable to fit the CVF with long-term memory. The GARCH model has the following formulation.

$$\begin{cases} x_t = f(t, x_{t-1}, x_{t-2}, \cdots) + u_t \\ u_t = z_t\sqrt{h_t} \\ h_t = w + \sum_{j=1}^{q} \lambda_j u_{t-j}^2 + \sum_{i=1}^{p} \eta_i h_{t-i} \end{cases} \tag{4}$$

where λ_j and η_i are parameters.

2) DEVELOPMENT OF AR-GARCH MODEL

When using the GARCH model to fit the residual sequence $\{u_t\}$, $\{u_t\}$ must have a zero mean, being a pure random and heteroscedastic sequence. Sometimes, the regression function $f(t, x_{t-1}, x_{t-2}, \ldots)$ cannot fully extract related information from the original sequence, and $\{u_t\}$ is likely to be autocorrelative rather than pure random. In such conditions, an autoregressive model is needed to fit $\{u_t\}$.

The autoregressive model is usually abbreviated as the AR model, which is used to describe the correlation in the sequence. The AR(1) denotes the one-order autoregressive model, while the AR(2) denotes the two-order autoregressive model. Similarly, AR(m) denotes the m-order autoregressive model. The AR model can describe the correlation between before and after in the sequence, namely, the relation between what happens at present and what happened in the past, where this relation is transferred forward. As for the R-R interval sequence, there is autocorrelation because of the driver's physiological characteristics. In addition, there is also autocorrelation in the residual R-R sequence, which means that the present fluctuations are affected by past fluctuations. The AR(m) model for the residual sequence $\{u_t\}$ is as follows:

$$u_t = \sum_{k=1}^{m} \rho_k u_{t-k} + e_t \tag{5}$$

where e_t is the autoregressive residual sequence, ρ_k is a parameter, and m denotes the number of order.

Because there is the ARCH effect in the residual R-R interval sequence, the variances of u_t and e_t are all non-homogeneous. Hence, the GARCH model that fits e_t is as follows.

$$\begin{cases} e_t = z_t\sqrt{h_t} \\ h_t = w + \sum_{j=1}^{q} \lambda_j e_{t-j}^2 + \sum_{i=1}^{p} \eta_i h_{t-i} \end{cases} \tag{6}$$

Overall, the developed AR(m)-GARCH(p, q) model for the R-R interval sequence is

$$\begin{cases} x_t = f(t, x_{t-1}, x_{t-2}, \cdots) + u_t \\ u_t = \sum_{k=1}^{m} \rho_k u_{t-k} + e_t \\ e_t = z_t\sqrt{h_t} \\ h_t = w + \sum_{j=1}^{q} \lambda_j e_{t-j}^2 + \sum_{i=1}^{p} \eta_i h_{t-i} \end{cases} \tag{7}$$

In (7), m is the autoregressive order of the residual sequence; q denotes the moving average order of the residual square sequence; p is the autoregressive order of the heteroscedasticity function.

Larger values of m, q and p make the model more complex and calculations time-consuming. The first-order model is simple in form and can be calculated quickly, which is useful to reduce the estimation time and increase the real-time recognition ability. Accordingly, the first-order

TABLE 4. Fitting results of the AR(1)-GARCH(1, 1) mode.

Parameters	Parameter values	Standard error	Z-statistic	R^2
c	0.6615	—	—	
ρ	0.9814	0.0020	314.8002	
w	2.21×10^{-6}	2.84×10^{-8}	77.8634	0.96
λ	0.2968	0.0042	70.2032	
η	0.7003	0.0028	247.8627	

model is selected when we developing the model, namely the AR(1)-GARCH(1, 1) model.

3) AR (1)-GARCH (1, 1) MODEL

Based on the analysis in subsection ''Data analysis'', we can see that in ideal road conditions, the R-R interval sequence fluctuates around a fixed value, and this fixed value can be seemed as deterministic information, also known as the average value of R-R intervals. Therefore, the following model can be used.

$$x_t = c + u_t \tag{8}$$

where c is the mean value of R-R intervals, and u_t is the residual sequence.

Therefore, the AR(1)-GARCH(1, 1) model is created for the R-R interval sequence x_t:

$$\begin{cases} x_t = c + u_t \\ u_t = \rho u_{t-1} + e_t \\ e_t = z_t\sqrt{h_t} \\ h_t = w + \lambda e_{t-1}^2 + \eta h_{t-1} \end{cases} \tag{9}$$

where c, ρ, w, λ and η are parameters of the model.

B. ARCH EFFECT TEST FOR AR(1)-GARCH (1, 1) MODEL

The ARCH effect test should be conducted for the AR (1)-GARCH (1, 1) model. The standard residual error z_t contains all information of the model. Therefore, if there is no ARCH effect in z_t, we can conclude that the ARCH effect has been eliminated, and the model is well fitted and has good stability.

The Lagrange Multiplier (LM) test is used to judge whether there is the ARCH effect in the model. The principle of the LM test is as follows: if the variance of the residual sequence is not homogeneous and exhibits the volatility cluster effect, the residual square sequence always has autocorrelation. The null hypothesis of the LM test is that the variance of the residual sequence is homogenous. Hence, the autoregressive model (ARCH (q)) is chosen to fit the residual square sequence:

$$e_t^2 = w_0 + \sum_{j=1}^{q} \alpha_j e_{t-j}^2 + r_t \tag{10}$$

where e_t is the residual sequence in (9), r_t is the autoregressive residual sequence, w_0 and α_j are parameters, and q denotes the moving average order.

Consequently, the homogeneity test for variance can be converted into the test of whether (10) is significant. If the equation is significant, it shows that the squared residual sequence has autocorrelation, that is, there is the ARCH effect. Otherwise, there is no ARCH effect.

C. RECOGNITION OF THE DRIVING FATIGUE STATE

After solving the AR(1)-GARCH(1, 1) model, the conditional variance h_t can reflect the fluctuations of the sequence well, and can be used to recognize changes in the driving state. If the difference between the conditional variance and mean variance is larger than three times the mean-standard deviation, we can conclude that the driving state changes from alert to fatigue.

Let v_a denote the mean value of the conditional variance of h_t, and σ_0 denote the mean-standard deviation. Then,

$$v_a = \frac{\sum_{t=1}^{n} h_t}{n}, \quad \sigma_0 = \sqrt{v_a} \tag{11}$$

If $(h_t - v_a) > 3\sigma_0$, it can be concluded that there is a significant change in the residual sequence of the R-R interval sequence at time point t, which indicates that there is a change in the driver's fatigue level.

IV. CASE STUDY

According to the models and recognition procedure in Section III, the recognition model for driving fatigue is developed and tested using field data in this section.

A. MODEL VALIDATION BASED ON THE DATA ON DRIVER 1

1) FITTING OF THE AR(1)-GARCH(1, 1) MODEL

Driver 1 drove an experimental vehicle from Baicheng City to Changchun City. The total driving time was 221 minutes and 20073 R-R interval data samples were collected. The sampled data is used to fit (9), where the results are shown in Table 4.

Hence, by substituting the parameter values in Table 4 into (9), the following equation can be obtained:

$$\begin{cases} x_t = 0.6615 + u_t \\ u_t = 0.9814 u_{t-1} + e_t \\ e_t = z_t\sqrt{h_t} \\ h_t = 2.21\times10^{-6} + 0.2968 e_{t-1}^2 + 0.7003 h_{t-1} \end{cases} \tag{12}$$

2) ARCH-LM TEST

Further, the Lagrange Multiplier (LM) test is used to judge whether there is the ARCH effect in the model

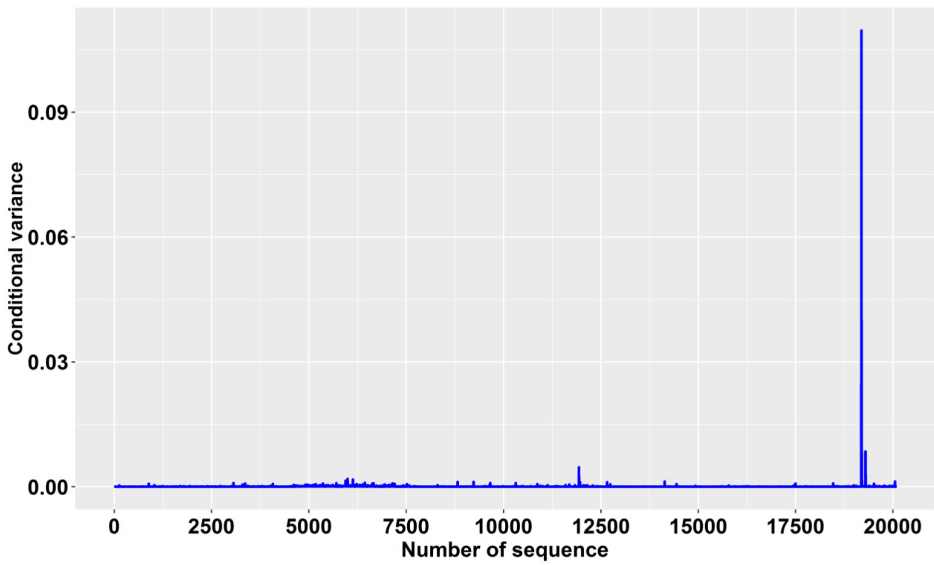


FIGURE 4. Conditional variance obtained from the R-R interval data of driver 1.

TABLE 5. Evaluation of the model based on the R-R interval data for the other 9 drivers.

Driver No.	2	3	4	5	6	7	8	9	10
Recognition time	11581	1606 3494	2674	3852	1940 4629	3752	2926	3688	7345
Real time	11405	1510 3320	2411	3631	1785 4505	3590	2723	3618	7215
Time delay	176	96 174	263	221	155 124	162	203	70	130

*Note: Recognition time is the output of the developed model; Real time is obtained by the investigators in the experimental vehicles; Time delay is the difference between Recognition time and Real time.

(ARCH-LM test). The F-statistic 2.0001 with P-value 0.1353 denotes the significance level of the equation, so it is used to conduct the test. We can accept the null hypothesis when the P-value is larger than 0.05. Therefore, the variance of the standard residual error sequence is homogenous, and the ARCH effect is eliminated.

3) RECOGNITION OF THE DRIVING FATIGUE STATE

The conditional variance changes of the AR(1)-GARCH(1, 1) are shown in Figure 4. We use v_a to denote the mean conditional variance of h_t, and σ_0 to denote the mean-standard deviation. Then,

$$\begin{cases} v_a = \dfrac{\sum_{t=1}^{20073} h_t}{n} \\ \sigma_0 = \sqrt{v_a} \end{cases} \tag{13}$$

By solving (13), we can obtain: $v_a = 8.78 \times 10^{-5}$, $\sigma_0 = 9.37 \times 10^{-3}$.

According to the recognition criterion $(h_t - v_a) > 3\sigma_0$, the time points that satisfy the recognition criterion can be obtained, which are $t = 1991$, 1992, 1993, 1994, and 1995.

Therefore, when t is between 1991 and 1995, the conditional variance of the model increases significantly. This means that there is a strong fluctuation in the R-R interval data. Under ideal road conditions, huge fluctuations only come from changes in the driver's fatigue state. Therefore, we can conclude that when t is between 1991 and 1995, the driving state increases from alertness to fatigue. In this study, the number of the R-R sequence samples does not directly correspond to the driving time. When t is between 1991 and 1995, the driving time is about 1914 s. According to the experiment's records, when the driving time is about 1800 s, the driver's state changed from alert to mild fatigue. Thus, the time delay of the established recognition model is 114 s.

B. MODEL VALIDITION BASED ON OTHER DRIVER'S DATA

The R-R interval data for the other 9 drivers is also used to validate the model. Due to limits, the fitting models and LM test results are not shown. The time delays of recognition are shown in Table 5.

From Table 5 we can see that the recognition of driving fatigue is correct in all cases. The time delays of recognition are all smaller than 5 minutes. The minimum delay is

70 seconds and the maximum delay is 263 seconds. There may be two reasons accounting for the time delays. The first is the recognition error produced by the AR (1)-GARCH (1, 1) model. The second is that the investigators asked the drivers and recorded their fatigue levels every 15 minutes. It is believed that if such enquiries were conducted every 1 minute, the time delays would be reduced to smaller values. However, the driving states would be disturbed significantly by the investigators in this case.

V. CONCLUSION

In this paper, the heart rate R-R interval sequence is chosen as an indicator to recognize the driving fatigue state. For the R-R interval sequence, it has the volatility cluster effect. Then, AR(1)-GARCH(1,1) model is used to analyze the sequence. According to the case study based on field data, the developed model can recognize the driving fatigue state timely. The following conclusions can be obtained from this study.

First, the R-R interval is an excellent indicator to recognize the driver's fatigue level. However, the raw data cannot be directly used to recognize the fatigue state, because only the volatility cluster effect of the R-R interval sequence is closely related to changes in the driving state.

Second, the AR(1)-GARCH(1,1) model is suitable to analyze the R-R interval sequence. The changes in the model's conditional variance are used to analyze the changes in the driver's fatigue level. The case study shows that the recognition time delay is smaller than 5 minutes, which is meaningful to provide early warnings when the driver falls into the fatigue state.

In the future, much attention should be paid to minimize the time delay of the recognition model. The performance of the model may be significantly improved when adopting R-R interval data together with other physiological indicators. Previous studies have validated the effectiveness of other indicators, which can provide valuable reference for the next study.

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LINHONG WANG received the B.E. degree in traffic engineering from Jilin University, Changchun, China, in 2007, and the Ph.D. degree in 2012. She is currently an Associate Professor with the School of Transportation, Jilin University. Her research interests include traffic safety and intelligent transportation systems.

JINGWEI LI received the B.E. degree in statistics from Shandong University, in 2017. He is currently pursuing the Ph.D. degree with the Department of Electronic Engineer, Stony Brook University, Stony Brook, NY, USA. His research involves machine learning method in big data.

YUNHAO WANG received the B.E. degree in economics from Shandong University, in 2016, and the master's degree in economics from Northeast Normal University, in 2019. He is currently an Research Associate with the Northeast Normal University, Changchun, China. His research involves data mining and econometrics.