RESEARCH ON CLASSIFICATION ALGORITHM OF REDUCED SUPPORT VECTOR MACHINE FOR DRIVING FATIGUE DETECTION

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ARTICLE DETAILS

ABSTRACT

In order to improve the accuracy and real-time performance of driving fatigue detection, a driving fatigue detection method is proposed based on reduced support vector machine algorithm. The ECG indicators are treated as human fatigue characterization indicators in the method. The human ECG can be obtained through experiment in different state, and PERCLOS value in selecting and controlling environmental conditions is taken as a basis for human fatigue state judging. Thus, the ECGdata from experiment can be divided into two categories of the normal and fatigue statue. Then integrating the ECG linear and nonlinear indicators establishes Identifiable eigenvector space, and the computational complexity is reduced by Reduced Kernel clustering method to improve robustness of the algorithm. The results of detection experiment on driving fatigue detection show the effectiveness of this method.

KEYWORDS

1. INTRODUCTION

Driving fatigue is one of the most common causes for traffic accidents. The present studies show that human physiology information can most accurately reflect the human's degree of fatigue. Analysis of human physical reaction in the process of driving fatigue combines with computer technology, psychology and medical etc. to investigate the method of measuring for driving fatigue from many aspects. That has very important practical significance and application value to prevent and avoid the traffic accident, keep the driver's work efficiency, protect the driver's physical and mental health. ECG signal acquisition with non-invasive and easy-carry characteristics is simple in all physiological information. With the advancement of monitor means and development of analysis technique, dynamic monitor and real-time processing will be fulfilled. So the evaluation and the detection of driving fatigue based on ECG signals become one of the research emphases. According to a study, HRV (Heart Rate Variability) analysis is the hot spot in the method of ECG signal detection and analysis. HRV which reflects the tensity and proportionality of cardiac sympathetic nerve and parasympathetic nerve refers to tiny fluctuation during the continuous heartbeat RR period [1]. And it is the best quantitative parameters to evaluate autonomic nervous activities [2]. Based on a study, the HRV of taxi driver under long-duration driving argue that HRV is closely related with driving fatigue [3]. A researcher points out there is significant correlation between frequency-domain parameters and the degree of fatigue when four ECG signal appeared [4]. When the human tired, the time-domain HRV parameters increased, LF increased, HF decreased and LF/HF increased. The authors believed that the increase in LF/HF was an indication of increase in degree of driving fatigue. A scholar investigated significant changes of HRV in the process of driving and combined with subjective evaluation to analyze the cardiac autonomic nerve function of participant under simulated driving [5]. Their foundlings suggested that there were significant differences among three parameters including increased LF, decreased HF, and increased LF/HF. The results manifested HRV is a sensitive index of psychological stress.

They proposed using HRV as a quantitative index of driving fatigue. A researcher monitored multiple physiological parameters, including HR, HRV, HF, LF, LF/HF, and VLF/HF parameters before and after driving task under in-door simulated static driving environment. The result of research showed that HRV, HF, and LF which are the sensitive index of psychological stress and poor microcirculation can be used as a quantitative index of driving fatigue. Based on a study, measured mental fatigue in drivers using ECG and EEG, and drew the conclusion that the approximated entropy of the ECG, and the lower and upper bands of power of heart rate variability (HRV) are significantly different before and after finishing the driving task [6]. Study showed the above research mostly used ECG signal based on linear hypothesis, but the normal heart movement has chaos kinematics law [7]. The current research can't completely describe the cardiac motion state with nonlinear composition. A researcher's foundlings indicated that parts of time-domain and frequency-domain presented obvious change trend [8]. And compared to nonlinear parameters, the change is much more obvious. While nonlinear parameters and linear parameters compared, the consistency of delivering the process and degree of fatigue is much better. It can be inferred that there are some changes in tensity and proportionality of cardiac sympathetic nerve and parasympathetic nerve. These changes can be reflected by trend of proposed HRV linear and nonlinearparameters. It drew the conclusion that it is feasible identifying driving fatigue based on ECG signal, but did not give a specific prediction method.

The fatigue samples in actual applying process of driver fatigue prediction are limited, so there are certain difficulties for state detection. Support vector machine (SVM) technology based on small sample statistical theory can solve the small sample learning problem, and has good generalization ability. One of the researcher has study on using SVM for automatic EEG detection of drowsiness during car driving [9]. The performance of SVM is influenced by not only kernel function and parameter selection but also by the number of support vectors. But fatigue detection system should identify driver's state timely and accurately. Therefore, this paper constructs a support vector classification method based on the kernel clustering Reduced, and validates the algorithm by experiment.

2. REDUCED SVM MULTI-VARIABLE'S CLASSIFICATION ALGORITHM

In this paper, driving state detection problem was changed into a classification problem using SVM classification algorithm. The main idea of SVM classification is to create a space optimal decision hyperplane, and the distance from the sample on both sides of it to the hyperplane is maximized to ensure that the SVM model has better generalization performance. For a given sample:

$$(x_i, y_i), i = 1, ..., l \qquad x_i \in R^d, y_i \in \{1, 2, ..., M\} \quad (1)$$

In the formula, x is the training sample, and y is the target class. M is the number of target class, l is the number of training samples, and d is the number of entered space dimensions. Constructing the optimal hyperplane classification problem is actually solving a quadratic programming problem under constraint condition, then the classification function can be expressed as:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i k(x_i, x) + b\right) \quad (2)$$

In this formula: b is the set over, α_i is the corresponding Lagrange multipliers. And $k(x_i, x)$ is the kernel function meeting condition. Its main role is to produce a linear high dimensional feature space for the complex pattern classification problem in a sufficiently high dimension feature space by nonlinear mapping conversion, and to find the largest Margin optimal decision hyperplane in this new space. But the SVM classification idea is for two types of classification. Multi-class classification must rebuild SVM classifier to solve, namely seeking a point belongs to $d\ R$, and divided into M parts of the rules. The common method is to transform gradually multivariate classification problems into binary classification problems, that is, multiple classifier composed of multiple binary classification SVM. In this study, multivariate classification problems can be transformed gradually into binary classification problems with 1-a-r classifiers (One-against-Rest Classifiers) which is a binary classification method through the structure of M binary target sub-classification method, thus establishing a dedicated multi-classifier consisting of multiple binary classification SVM. 1-a-r classification method is simple to establish but the imbalance of positive and negative training samples is more prominent when facing to the driver's state classification task [10]. Traditional SVM to solve such problem result in the circumstance that the optimal classification plane offset to the negative class collection because of the establishment of the division of positive class and negative class decision-making function. And the speed of classifier will be significantly reduced when there are a large number of support vectors. To solve the problem, this paper proposed a reduced separator method to simplify support vectors and accelerate the classification efficiency on the basis of the study of a researcher [11]. Firstly, two types of plus or minus support vector that need to be clustered in the feature space when creating a set of positive class and negative class. The positive (negative) support vector set waiting for clustering is set to $X = \{x1, x2, ..., xn\}(xi \in Rd, i = 1, ..., n)$. Clustering radius is set to is the nonlinear mapping from the points in the input space to feature space F. And $\varphi(xki), (i = 1, ..., nk)$ is support vector belonging to class Ck in feature space. $SetC1 = \{\varphi(x1)\}, O1 = \varphi(x1), Cluster_{num} = 1, Z = \{x2, ... xm\}$. Then select the sample $x_i \in Z$ and calculate the distance between $\varphi(xi)$ and the centroid of the k class:

$$O_k = (1/n_k)\sum_{p=1}^{n_k} \varphi(\tilde{x}_{k_p}) \quad (3)$$

$$d(\varphi(x_i), O_k) = \sqrt{k(x_i, x_i) - \frac{2}{n_k}\sum_{p=1}^{n_k} k(x_i, x_{k_p}) + \frac{1}{n_k^2}\sum_{p,q=1}^{n_k} k(x_{k_p}, x_{k_q})} \quad (4)$$

If $d(\varphi(xi), oj) \le r, \varphi(xi)$ is joined to the class $c\ j$. Then the centroid position can be recalculated. On this basis, the nearest centroid oj is found from $\varphi(xi)$. That is:

$$O_j = \arg_j \min_{k=1}^{Cluster\_num} d(\varphi(x_i), O_k) \quad (5)$$

In the formula, Cluster _ num is the number of classification to obtain the value of oj , and its initial value is set to 1. In the iteration process, when

$d(\varphi(xi), oj) > r$, a classification quantity should be added until $d(\varphi(xi), oj) \le r$. On the basis of the above study, the SVM classifier can be Reduced through centroid of the cluster formed after clustering instead of support vector within the cluster, which reduces the classification error caused by the imbalance of data collection. In addition, support vector should be Reduced keeping the original classifier generalization performance to improve SVM classifier speed. Define the vector $d_2 = [d_1^2, d_2^2, ... d_n^2 k]^T$ in the formula: $d_i(i = 1, ..., n_k)$ is the distance between the original image zk of ok and its close neighbor xk in the input space. The approximation of the centroid ok of the original image in the input space can be represented by the formula:

$$z_k = \frac{1}{2}E_1\Lambda_1^{-1}V_1^T(d_0^2 - d^2) + \overline{x} \quad (6)$$

In the formula z_k is the Centroid preimage, and $E_1 = [e1, e2, ... eq]$ is a dxq matrix composed of a set of standard orthonormal column vector ej. Column vector ci is set to the projection of vector $xk\ j - x$ on $E1$. Then $d_0^2 = [\||c1\||2, ..., \||c_k^n\||2]^T$.

In the above algorithm, the greater the clustering radius is, the less the number of clusters is. At the same time, the reduction rate of the support vector become higher, and classification hyperplane difference between before and after the reduction is greater, and the generalization performance lose more. Therefore, the size of the cluster radius plays a compromise part between the support vector reduction rate and the generalization performance loss. In actual operation, support vector ought to be reduction as much as possible through increasing the size of the cluster radius iteratively, while setting difference threshold and limiting the maximum that the separating hyperplane changes before and after simplification (To limit the generalization performance loss of the classifier). The difference between the original classification plane and formative hyperplanes is calculated in each iteration. If the difference between the two exceeds the difference threshold , the iterative simplifing process is terminated, and SVM classifier resulting in the first iteration is taken as final simplification SVM classifier. Otherwise, the clustering radius should be increased to reduct support vector further.

3. VIRTUAL DRIVING EXPERIMENT

3.1 Experimental subject selecting

We selected 8 male postgraduates from Zhejiang University in this study. The information of subjects is shown Table 1.

Items	Average
Age	28.8±3.2 (Year)
Height	171.6±6.8(cm)
Weight	71.3±7.7(kg)

Table 1: Characteristics of subject

3.2 Variables

The independent variables were SDNN, LF, HF, LF/HF, LFnorm, HFnorm, the C0 and sample Entropy of nonlinear parameters of RR interval time series R, and C0 and sample Entropy of nonlinear parameters of R-wave peak sequence. SDNN which reflects the autonomic nervous (including the sympathetic nerve and vagus nerve) total tension evaluates the damage and restoration of autonomic nervous system.

3.3 Experimental task

The virtual driving platform was used for virtual driving through the software *3D Driving School 3.1* in the process of experiment. Choose highway and country road two scenes as virtual driving task and ask the subjects to drive according to actual traffic regulate and law.

3.4 Experimental equipment

ECG data was collected through the Flex Comp system of Canadian Thought Company. Meanwhile, in this study, we expect to use eye tracker to capture human eye state in the process of driving. Eye tracker is mobile eye tracking system with 25/30 Hz of sampling rate. The signal collecting device connected with recording equipment device through single cable. In the test, the subjects wore the equipment's and sat naturally at the front of high speed tester. After acquisition system began to work, the

equipment can analyse eye-movement video, the coordinate of fixation point and auxiliary information. And the data finally saved in the hard disk or external video equipment.

3.5 Experimental procedures

The experiment is finished in similar two sessions of human physiology cycle: 9:00~12:00 AM and 2:00~5:00 PM. Maintain environment temperature at 22±2 centigrade, make sure the virtual driving environment has good light and keep quiet in the process of experiment. Collect the ECG signal in the way of Chest-linked method, after pasting the electrode, we helped the subjects to wear the helmet eye tracker and adjust to the appropriate location to capture the eye image. Obtained the ECG signal as standard after the subjects sat 10 minutes naturally. Virtual driving task lasted 120 minutes, and we recorded ECG and eye movement signals according to time sequence in a virtual driving the process. Experiment process is shown in Figure 1.

Figure 1: Experimental scene

Stop the experiment 5 minutes later if the below states were presented in the virtual driving process

(1) The subjects felt uncomfortable strongly;
(2) The subjects frequently cleaned eyes, yawned, nodded and closed eyelid slowly and did other external actions
(3) Observe the interface of driving task, the number of the software alertsand obvious increased the number of driving task termination

At the end of the experiment task, rested fifteen minutes.

4. DATA PROCESSING AND ANALYSES

During the experiment, due to the impact of helmet eye tracker, eight subjects who appeared obvious fatigue did not reach the time of the virtual driving tasks, six of all subjects' experimental time is 60 minutes -70 minutes, then another two subjects felt uncomfortable strongly in 30 minutes and the experiment had to be stopped. ECG signal and six eye-movement videos over 60 minutes are regarded as an analytical object in data analysis process.

4.1 Analysis of eye-movement data

PERCLOS refers to percentage of eyelid closure over the pupil over time. There are three type of measurement (P70, P80, and EM). Three ways are defined as follows.

P70: The degree of eye closure is greater than or equal to 70% of the proportion of time.

P80: The degree of eye closure is greater than or equal to 80% of the proportion of time.

EM: The degree of eye closure is greater than or equal to 50% of the proportion of time.

Research has shown that P80 and driving fatigue are highest correlated in parameters of PERCLOS. In this study, we also use the P80 algorithm to

judge the fatigue. In practical applications, the degree of eye closure commonly was expressed by pupil opening degree, namely the ratio of the visible vertical pupil size and maximum pupils. The measuring principle of P80 algorithm in PERCLOS is shown in Figure 2.
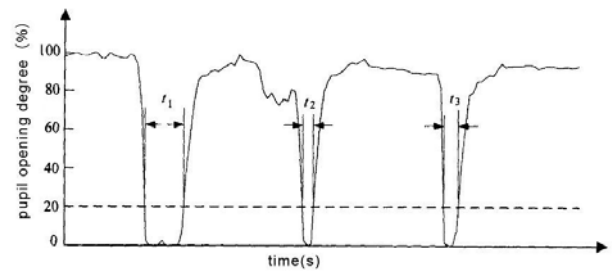

Figure 2: Measuring principle of P80 algorithm

Assume that there are n times eye closure in continuous sampling period T, and time for 20% of pupil closed to 20% pupil opened is, then PERCLOS values can be obtained by the following formula: i t

$$PERCLOS = \sum_{i=1}^{n} t_i \Big/ T \qquad (7)$$

In this study, we used the approximation algorithm. Assumed that collected N eye image in unit-time, determined that the eye was opened or closed after the analysis and identification. Defining the eye pupil opening degree is greater than 20% is opened while pupil opening degree equal to 20% or less is closed. Let the number of closed pictures is n, then PERCLOS values in unit-time can be got through the following formula:

$$PERCLOS = n \Big/ N \qquad (8)$$

After obtaining PERCLOS value, we can get any time or period of fatigue by Table 2.

Table 2: PERCLOS evaluation criteria

Fatigue status	PERCLOS value
Sobriety	PERCLOS<0.075
Suspected fatigue	0.075<PERCLOS<0.15
Fatigue	0.15<PERCLOS

4.2 ECG signal processing

Data sampling rate is 1024 Hz. In this study, because heart linear and non-linear parameters of the length of the data requirements, we took total 70 minutes of virtual driving process ECG signal, including the first 60 minutes and 10 minutes of sit quietly. In order to ensure the results of real-time, a former signal 10th second was regarded as the beginning of the latter signal data segment, that is, there were 20 second overlaps between the former and latter data segment. The ECG should be calculated with time-domain, frequency-domain and the nonlinear parameters respectively after filtering, noise removal, R wave detection. There were 80 data segments after the data processing from every Experimental subject, and a set of experimental data (10 indexes) can be acquired from each data segment. According to the corresponding evaluation criteria of Table 3, 10 groups of signals were selected in each driving condition of each subject randomly. The test set was comprised of 30 groups of the signals, and the rest of 70 groups of signals was the training set. The training set was divided into 10 equal parts. One part was kept verifying the performance of the model, and the remaining 9 parts were used to train the model.

Due to personal physical constitution, environmental and other factors, each of ECG value is very different. To eliminate the impact of these factors on the data and get the fair criteria for the result, we used mean-variance standardization method to handle the measurement signal, and then the processed signal has characters of zero mean and unit variance criterion. We will get the state of fatigue by eye movement data, and the results of

the above ECG signal processing can be divided into 3 categories according to sober, suspected fatigue, and fatigue. Then the prediction can be done with reduced support vector classification method. Kernel function is selected with the Gaussian kernel when classification training using support vector, and the difference threshold = 0.15. Two study parameter values can be got after optimization using method of cross-validation. And = 156, = 0.5. Then the data sets can be tested with the reduced SVM classification method the proposed in this paper. The correct rate of detection of subjects is shown in Table 3:

Table 3: The correct rate of driving state detection of 6 subjects

subject	Driving state			total
	A	B	C	
1	100	80	90	90
2	90	90	70	83.3
3	90	60	80	76.7
4	90	80	90	86.7
5	80	90	100	90
6	90	90	100	93.3
total	90	81.7	88.3	

4.3 Analysis of results

To reduce the number of support vector effectively, this paper presents a reduced SVM method which can increase SVM classifier speed based on remaining classification accuracy of SVM and ensure quick identification of driving state. From the experimental results, detection correct rate of each subject overall is 76.7% to 93.3%. This shows the method proposed in the paper can identify the driving condition in a high detection rate, but there is a relatively large distance from research in laboratory to the practical application. Firstly, 100% rate for fatigue detection must be done in order to guarantee driving safety. Secondly, adopting PERCLOS method does not distinguish completely normal samples and fatigue samples due to the complexity of fatigue situation. Thirdly, physiological indicators and behavioural indicators of human fatigue state are not entirely consistent. These are likely to result in identification error of classified sample. How to choose a more accurate characterization of fatigue indicators is one of the main contents of the study next stage. In specific state detection operation, there are not yet perfect method on constructing kernel function and selecting the optimal parameters of the separator. So, the study on reduced SVM algorithm in future will focus on how to choose the optimal classifier parameters, for example difference threshold, and optimize the kernel function, ensuring the optimal generalization capacity, maximum reduction rate and classification accuracy.

5. CONCLUSION

This paper proposes a driving fatigue detection method based on reduced SVM algorithm for improving accuracy and real-time of driving fatigue detection. The ECG indicators are treated as human fatigue characterization indicators in the method. The human ECG can be obtained through experiment in different state, and PERCLOS value in selecting and controlling environmental conditions is taken as a basis for human fatigue state judging. Thus, the ECG data from experiment can be divided into two categories of the normal and fatigue statue. Then integrating the ECG linear and nonlinear indicators establishes Identifiable eigenvector space, and the computational complexity is reduced by Reduced Kernel clustering method to improve robustness of the algorithm. The results of experiment on driving fatigue detection show the effectiveness of this method.

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