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DRIVER FATIGUE DETECTION USING APPROXIMATE ENTROPIC OF STEERING WHEEL ANGLE FROM REAL DRIVING DATA

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Abstract

This paper presents a steering-wheel-angle-based driver fatigue detection method for real driving conditions. This method extracts approximate entropy (*ApEn*) feature from recorded steering wheel angle (SWA) signal with a decision-tree-like classifier to identify the driving fatigue level. *ApEn* is extracted from fixed-size sliding window on real-time SWA series. To further exploit the in-depth information of SWA, additional features including interval-percentage, deviation, kurtosis and complexity value of *ApEn* are extracted and applied to the designed classifier. The experiment is set on 14.68 h of real road driving, the collected data has been segmented into three fatigue levels ("awake", "drowsy", "very drowsy"). The classification result showed that the proposed method achieves an averaged accuracy of 82.07%. These results confirm that the proposed method is effective in the detection of real-time driver fatigue.

Key Words

Driver fatigue, steering wheel angle (SWA), approximate entropy (*ApEn*), fatigue detection

1. Introduction

Drowsy driving has caused 35%–45% of road accidents, especially when driver is sleepy and tired [1]. Driving fatigue is a depleted stage in which driver's abilities in perception, decision and control significantly degrades [2], thus largely raising the accidental risks. Today, studies have paid increasing attention to real-time detection of driver fatigue in an effort to reduce traffic accidents.

Recently, some studies have focused on the detection methods based on vehicle status measurements [3], which are non-intrusive. Steering wheel angle (SWA), steering wheel movement (SWM) and standard deviation of lane position (SDLP) are commonly monitored vehicle status according to current fatigue level detection technologies. The vehicle-status-based fatigue detection method is favourable regarding its reliability, real-timeness and non-invasiveness. SWM method uses an angle sensor mounted on the steering column [4]. However, SWMs have been adopted but work only in very limited situations [5]. SDLP, another measurement, evaluates driver fatigue by tracking vehicle lateral position within the lane [6]. However, there are two major limitations for this method: firstly, the consistency of SDLP-fatigue correlation is low across individuals; secondly, SDLP only accounts for the external behaviour of vehicle regardless of driver's control activity.

The above-mentioned methods showed good performance in simulated driving environment. However, their effects in real driving condition remain doubtful. Previous studies scarcely focused on SWA data in real driving for driver fatigue detection, which is inherently non-linear, time-variant and space-variant. Non-linear dynamic analysis [7]–[10], compared to classical linear time series analysis methods, can provide complementary information of the dynamic process. As a novel non-linear dynamic analysis method, approximate entropy algorithms have become popular and is proved to be robust for evaluating irregularity or predictability of time series [11].

In this paper, a real-time driver fatigue detection method using SWA data is proposed. This method extract in-depth features of SWA data to improve detection accuracy. Firstly, we observe SWA time series in a fixed-size time window and extract approximate entropy. Then, we calculate four approximate entropy-based features, namely, interval-percentage, deviation, kurtosis and complexity value of the approximate entropy series. Lastly, we apply the extracted statistic features on a decision-tree-typed classifier to determine the driver fatigue level by "awake", "drowsy" and "very drowsy".

We construct this paper as follows: Section 2 firstly reviews the approximate entropy calculating method for non-linear dynamic process, then introduces the proposed fatigue features extraction method based on approximate entropy series, followed by the design of fatigue level classifier. Section 3 shows the experiment results on collected

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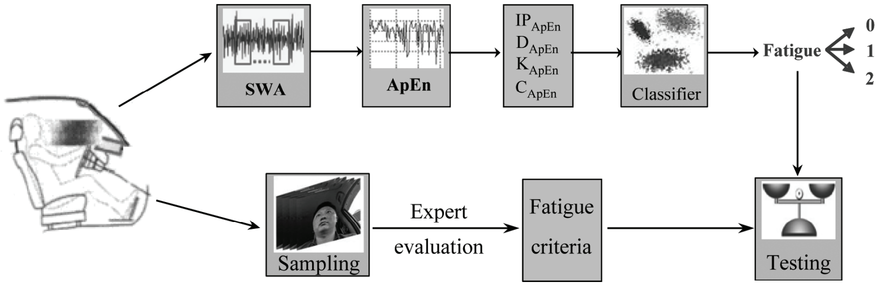


Figure 1. SWA-based fatigue detection method.

SWA data from mounted sensors in a vehicle. Section 4 concludes this paper.

2. Methodology

Figure 1 demonstrates the procedures of the SWA-based fatigue detection method. First step, extract the approximate entropy from SWA time series within fixed-size time windows. Second step, calculate four statistic approximate-entropy-derived features. Third step, apply the statistic features on a decision-tree-like classifier to determine the driver fatigue level by "awake", "drowsy" and "very drowsy". Finally, verify the classifier performance with expert evaluation.

2.1 Approximate Entropy of Steering Wheel Angle

Previous works [12]–[14] proved that the steering wheel control behaviour of a drowsy driver manifests evident abnormal features compared with those in wakeful state. The steering wheel angle (SWA) data, used for analysis and recognition of driver's fatigue state, is usually in the form of dynamic stochastic process. The non-linear and in-depth information hidden in SWA data is deemed valuable in terms of detecting driver fatigue.

Irregularity analysis has become an effective approach for non-linearity evaluation for dynamic signals. Here, the approximate entropy ($ApEn$) is used to quantify the irregularity of stochastic SWA time series. The reasons for using approximate entropy include: (1) a variety of studies have shown the efficiency of approximate entropy on quantifying complexity and irregularity of stochastic time series and (2) some researchers found that approximate entropy can successfully characterize variation within the physiological and behavioural processes of drivers [11], [15].

Robust estimation of approximate entropy of short noisy time series data is given by the following (take SWA data for example):

$$
\begin{aligned}
ApEn_{SWA}(m,r,N) &= \frac{1}{N-m+1}\sum_{i=1}^{N-m+1}\log(C_i^m(r)) \\
&\quad - \frac{1}{N-m}\sum_{i=1}^{N-m}\log(C_i^{m+1}(r)) \\
C_i^m(r) &= \frac{B_i}{N-m+1} \qquad (1)
\end{aligned}
$$

where m is the number of embedded dimensions, r is the scale or tolerance, N is the number of data points in time space or the length of the input time series and B_i is the number of j satisfying $\{d(X(i),X(j)) \le r\}$, wherein $X(\cdot)$ represents the m-dimensional vector extracted from the input SWA time series:

$$
\begin{aligned}
X(i) &= [X_{SWA}(i), X_{SWA}(i+1), \ldots, X_{SWA}(i+m-1)], \\
&\quad X_{SWA}(i) \in R^m \\
X(j) &= [X_{SWA}(j), X_{SWA}(j+1), \ldots, X_{SWA}(j+m-1)], \\
&\quad X_{SWA}(j) \in R^m \qquad (2)
\end{aligned}
$$

and $d(X(i),X(j))$ is a measure of the distance between vectors $X(i)$ and $X(j)$, $i,j=1,\ldots,N-m+1$. Define the distance as the maximum difference between the corresponding elements in two vectors.

In the calculation of $ApEn$, the increase of m will heavily add up to the computational load. When driver is fatigued, the instantaneous variation of steering wheel angle will decrease, which further influences the $ApEn$ value. Regarding the parameter value in $ApEn$ calculation, we refer to the work of Yentes *et al.* [16] and choose $m=2$, and refer to the work of Pincus [17] and choose $r=0.2*SD$, where SD is the standard deviation of the original fixed-size sliding window (2 s).

2.2 Structural Statistical Features Extracted from $ApEn$

According to (1), the calculation of $ApEn$ is actually measuring the probability of new patterns in time series when embedded dimensions change. The higher the probability, more complex the time series is. When the driver is drowsy, it is assumed that the frequency of SWA variation will decrease thus diminishing $ApEn$. To capture the abnormal variation of steering wheel angle when driver becomes fatigued, we select the interval percentage, deviation, kurtosis and complexity of $ApEn$ as critical features and apply them to a classifier for fatigue recognition.

2.2.1 Interval Percentage of ApEn

The interval percentage of approximate energy is defined as

$$
\begin{aligned}
IP_{ApEn} &= \frac{1}{W}\sum_{i=1}^{W} p_i \\
p_i &= \begin{cases} 1, & \text{if } ApEn_i \in [0.6\ 1] \\ 0, & \text{if } ApEn_i \notin [0.6\ 1] \end{cases} \quad i=1,\ldots,W
\end{aligned} \qquad (3)
$$

where W is the number of short sliding windows contained in a SWA data segment; p_i is either 0 or 1 according to the $ApEn$ of the ith window.

2.2.2 Deviation of ApEn

Deviation is often used to measure the statistical dispersion in probabilistic aspect . IP_{ApEn} described above represents the intensity of $ApEn$ in a given interval, but does not reflect the distributive characteristic of a group of $ApEn$s. To further explore the statistical information under $ApEn$, the deviation of $ApEn$ is defined as

$$D_{ApEn} = \frac{1}{W}\sum_{i=1}^{W}(ApEn_i - \mu)^2 \tag{4}$$

where W denotes the number of short sliding windows contained in a SWA segment, $ApEn_i$ is the approximate energy in the ith window, and μ is the average value of $ApEn_i$ of the SWA segment.

2.2.3 Kurtosis of ApEn

In recent years, kurtosis, as an indicator of statistical distribution, is widely applied in signal analysis [18], [19]. Analysing kurtosis coefficient of $ApEn$ can help observe the instantaneous fatigue during driving. Kurtosis of $ApEn$ is defined as

$$K_{ApEn} = \frac{1}{W}\sum_{i=1}^{W}\left(\frac{ApEn_i - \mu}{\sigma}\right)^4 \tag{5}$$

where W represents the number of short sliding windows contained in a SWA segment; $ApEn_i$ is the approximate energy in the ith window; μ and σ represent the average value and standard deviation of $ApEn_i$ of the SWA segment, respectively.

2.2.4 Complexity of ApEn

Complexity reflects the intricacy level of a dynamic system. We calculate the complexity of $ApEn$ series to describe the state transition of driver's steering wheel control behaviour. The complexity of $ApEn$ is defined as

$$C_{ApEn} = \frac{c(n)\log_2(n)}{n} \tag{6}$$

where $c(n)$ represents the complexity of the $ApEn$ in a SWA segment, of which the computation method is described in [20]; n is the length of a symbol series. The time series are converted into a binary sequence B in this paper is formulated as

$$B_i = \begin{cases} 1, \text{ if } ApEn_i > 0.7 \\ 0, \text{ if } ApEn_i \leq 0.7 \end{cases} \tag{7}$$

where $ApEn_i$ is the approximate energy in the ith window in an SWA segment.

2.3 Fatigue Level Detection

In this section, we first set up the criteria to evaluate fatigue level based on expertise. After that, we propose an $ApEn$-feature-based fatigue level detection model to determine driving status from given SWA time series. Finally, we evaluate the proposed classifier.

2.3.1 Criteria of Fatigue Level Evaluation

In this paper, we define three fatigue levels: awake, drowsy and very drowsy. The most practical method to label the driver's fatigue level is to determine the fatigue levels according to driver's facial expression and head movement by trained experts. Wierwille *et al.* [21] and Qu and Chen [22] verified the effectiveness of such evaluation method with regard to statistic consistency. This criteria system is adopted in this paper to rate the fatigue level a designated driver facial video clip.

2.3.2 Fatigue Level Classification

To classify the fatigue levels based on the extracted entropic features from SWA data, we design the following fatigue level evaluation model:

$$F_{label} = F_1 + F_2, F_1, F_2 \in (0, 1) \tag{8}$$

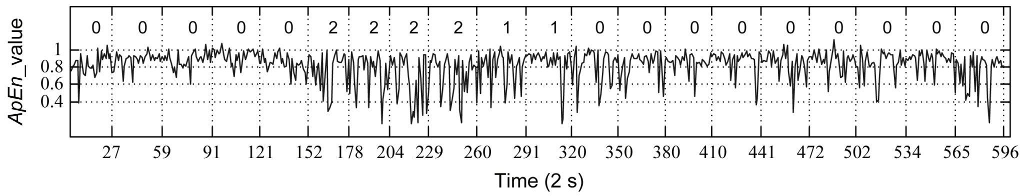
where F_{label} is the output fatigue level, $F_{label} \in (0, 1, 2)$. Three fatigue levels: awake, drowsy very drowsy, are labelled "0" , "1" and "2", respectively. F_1 and F_2 are obtained from (9)–(12).

$$F_1 = \begin{cases} 0, & \text{if } (IP_{ApEn} \geq 0.8) \\ 1, & \text{if } (IP_{ApEn} \leq 0.7) \\ 0, & \text{if } (D_{ApEn} < Q \mid 0.7 < IP_{ApEn} < 0.8) \\ 1, & \text{if } (D_{ApEn} \geq Q \mid 0.7 < IP_{ApEn} < 0.8) \end{cases} \tag{9}$$

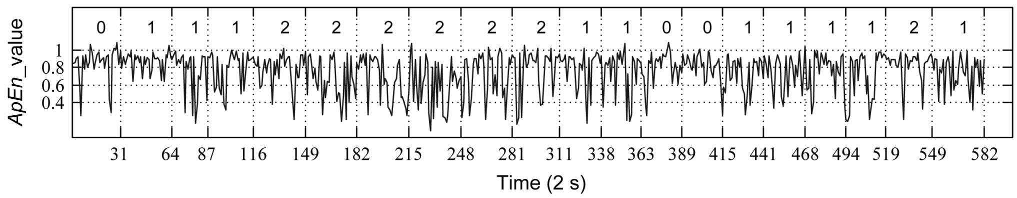
Q is the threshold of $ApEn$. In this study, we optimize $Q \in [0.3\ \ 0.45]$ to gain best classification accuracy from the training set. If the driver is overactive, the threshold is higher. Then, we need to renew the output of F_1 by

$$F_1 = \begin{cases} 1 \to 0, & \text{if } (|D_{ApEn_{i-1}} - D_{ApEn_i}| > T_1 \\ & \text{and } |D_{ApEn_i} - D_{ApEn_{i+1}}| > T_1) \\ 0 \to 1, & \text{if } (|D_{ApEn_{i-1}} - D_{ApEn_i}| > T_2 \\ & \text{and } |D_{ApEn_i} - D_{ApEn_{i+1}}| > T_2) \\ \sim (0,1), & \text{if } (K_{ApEn} > K) \end{cases} \tag{10}$$

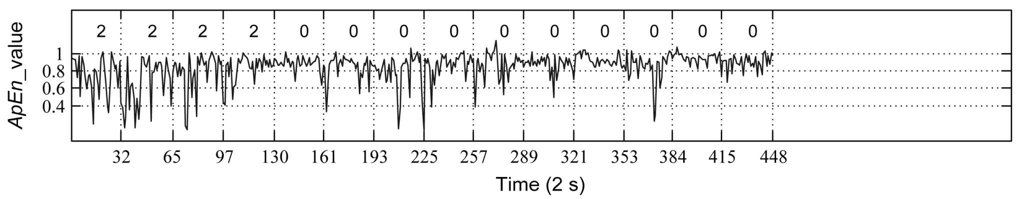
where i denotes the sample index. T_1 and T_2 are thresholds reflecting the adjacent difference between $ApEn$ deviation, valued at $T_1, T_2 \in [0.01\ \ 0.04]$ to be optimized in our study. K is the kurtosis threshold of $ApEn$, of which the value



(a)



(b)



(c)

Figure 2. An example of ApEn distribution. The numbers 0, 1 and 2 represents fatigue levels "awake", "drowsy" and "very drowsy".

reflects the irregularity of the fatigue level, valued at $K \in [7\ \ 10]$ to be optimized in our experiment. Generally, this value tends to be higher if the driver is more active.

$$F_2 = \begin{cases} 1, & \text{if } (C_{ApEn} > C \text{ and } K_{ApEn} \leq K) \\ 0, & \text{if } (C_{ApEn} < C \text{ and } K_{ApEn} \leq K) \end{cases} \tag{11}$$

where C is the complexity threshold of $ApEn$. According to our experiment, $C \in [1\ \ 1.2]$. Generally, overactive drivers tend to exhibit higher C. Here K is the same with that in (10). We need to renew the output of F_2 by

$$F_2 = \begin{cases} 1 \to 0, & \text{if } (|C_{ApEn_{i-1}} - C_{ApEn_i}| > M_1 \\ & \quad \text{and } |C_{ApEn_{i+1}} - C_{ApEn_i}| > M_1) \\ 0 \to 1, & \text{if } (|C_{ApEn_{i-1}} - C_{ApEn_i}| > M_2 \\ & \quad \text{and } |C_{ApEn_{i+1}} - C_{ApEn_i}| > M_2) \end{cases} \tag{12}$$

where i is the sample index. M_1 and M_2 represent the thresholds reflecting the adjacent difference between $ApEn$ complexity, valued at $M_1, M_2 \in [0.4\, 0.7]$ to be optimized in this study. In our method, all the parameter settings are obtained through the test samples learning.

2.3.3 Classifier Evaluation

The prediction accuracy of a designated test set is usually used to measure the prediction ability of a classifier. The classification accuracy is calculated as

$$A_{classifier} = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%, \tag{13}$$

where TP is the number of true-positives, TN is the number of true-negatives, FP is the number of false-positives and FN is the number of false-negatives. Accuracy, resulted from this equation, indicates an overall detection accuracy on both positive and negative samples.

3. Experiment and Results

We conducted $ApEn$ computing to all the samples and take Subject 6 as an example, whose $ApEn$ distribution of the SWA time series under real driving conditions is shown in Fig. 2. There are three sub-graphs, each with a horizontal axis representing numbers of short time window of the sample and a vertical axis representing computing results of $ApEn$ of each window. Numbers 0, 1 and 2, respectively, represent the three fatigue levels, namely awake, drowsy and very drowsy, of the driver in one piece of sample data, which come from the expert's evaluation. The $ApEn$ distribution of Subject 6's fatigue states in the first 20 samples are demonstrated in Fig. 2a, the second 20 samples in Fig. 2b and the last 14 samples in Fig. 2c. From these graphs, we can see that when the driver is in the "awake" state, "0", the $ApEn$ values of SWA data mainly distribute in the interval [0.8 1], and in the "very drowsy" state, "2", those values distribute more widely in the interval [0.4 1]. Meanwhile, when the driver is in the "drowsy" state, "1", the distribution range of those values stands between those of "0" and "2". To conclude, it shows evidence that the $ApEn$ value distribution of driver's SWA data represents prominent difference between fatigue levels. We therefore drive in more details into the $ApEn$ to mine driver's fatigue features from SWA data and detect fatigue level.

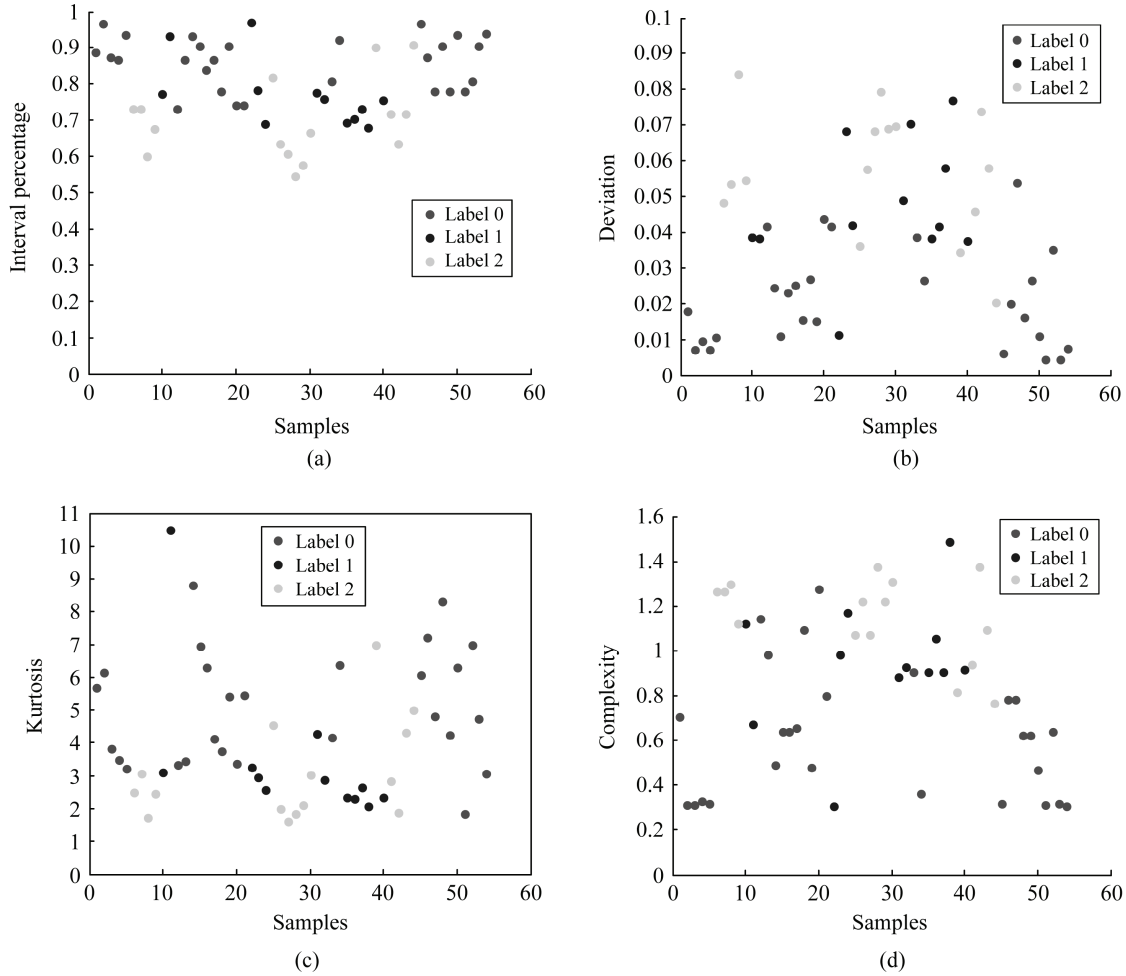


Figure 3. An example of statistics features distribution: (a) interval percentage; (b) deviation; (c) kurtosis and (d) complexity.

Figure 3a shows one driver's IP_{ApEn} distribution. According to (3), IP_{ApEn} represents the percentage of $ApEn$ values distributed in interval [0.6 1] for each sample. The darkest stars represent "awake", the lighter stars represents "drowsy" and the lightest stars, "very drowsy". Here we can see that the IP_{ApEn} values of "awake" are generally high and those of "very drowsy" are low, while those of "drowsy" state lie on in between the two states. We can also see that the percentage of distributions in a given interval is distinctively different for drivers at different fatigue levels. Figure 3b shows D_{ApEn} distribution for a subject's SWA data. D_{ApEn} represents the dispersing degree of $ApEn$ for this observed sample calculation in (4). As shown in this figure, the D_{ApEn} values of "awake" are generally low, those of "very drowsy" are generally high, and those of "drowsy" stand in between. It also shows evidence that the $ApEn$ deviance value distributions of drivers at different fatigue levels are distinctively different. Figure 3c shows K_{ApEn} values of a subject's SWA data. K_{ApEn} represents statistic features of $ApEn$ value distribution of this observed sample calculated in (5). As shown in this figure, K_{ApEn} values are mostly high when the driver is "awake", low when the driver is "very drowsy", and in between when the driver is "drowsy". It shows evidence that the driver's K_{ApEn} values have different distribution tendency when the driver has different fatigue levels. Figure 3d demonstrates the C_{ApEn} value of a subject's SWA data. C_{ApEn} represents the complexity of this observed sample calculation in (6). As shown in this figure, C_{ApEn} values are generally high when the driver is "awake", low when the driver is "very drowsy" and in between when the driver is "drowsy". It also shows that the C_{ApEn} distribution ranges of the driver in different fatigue states are eventually different.

The detection results of the proposed method are evaluated in confusion matrices. The expert's classification is referred on the columns, the performance of the proposed method is represented on the rows. The purpose here is to discover a good compromise between a high detection rate of fatigue level and a low number of false alarms. Indeed, low detection rate of fatigue level is potentially dangerous for the driver, but a large number of false alarms may discredit the system, and the experiment will then not pay attention to true alarms.

According to different fatigue levels shown on the subjects, the test results based on SWA data are divided into two parts. One is shown in Table 1, containing test results of all samples from the subjects with fatigue "Awake" and "Drowsy" and the other part is shown in Table 1, containing those from the subjects with all three

Table 1
Confusion Matrix of the Approximate Entropy based for Detection Drowsiness Status "Awake" and "Drowsy"

		Expert Classification	
		"Awake"	"Drowsy"
Detection results	"Awake"	94.44%	31.58%
	"Drowsy"	5.56%	68.42%
	Samples	72	38

Table 2
Confusion Matrix of the Approximate Entropy based for Detection Drowsiness Status
"Awake", "Drowsy" and "Very Drowsy"

		Expert Classification		
		"Awake"	"Drowsy"	"Very drowsy"
Detection results	"Awake"	87.50%	14.70%	10.71%
	"Drowsy"	12.50%	79.41%	25%
	"Very drowsy"	0.00%	5.89%	64.29%
	Samples	40	34	28

fatigue levels. The samples in Table 2 total 110, with 72 at level "Awake" and 38 at "Drowsy", coming from 4 subjects. As shown in this table, the detection correctness of the fatigue "Awake" is 94.44%, with error rate at 5.56% and the correctness of "Drowsy" is 68.42%, with error rate at 31.58%. Table 2 contains 102 samples, 40 of which are at "Awake", 34 at "Drowsy" and 28 at "Very drowsy", coming from 2 subjects. From this table, we can see the detection correctness reaches 87.5% for samples at "Awake", with an error rate at 12.5%; correctness 79.41% and error rate 20.59% for samples at "Drowsy", and correctness 64.29% and error rate 35.71% for "Very drowsy". In total, the average correctness of all the test samples arrives at 82.07%.

4. Conclusion and Future Work

This paper proposes a detection system of driver fatigue using SWA information recorded by built-in sensors in the vehicles, which undergo a real-road driving test lasting approximately 15 h. The data contain three fatigue levels including "awake", "drowsy" and "very drowsy", which have been examined by related experts according to the facial expressions, mental state of a driver and head position. The proposed method extracts IP_{ApEn}, D_{ApEn}, K_{ApEn} and C_{ApEn} to represent the driver's situation to determine the fatigue level of the driver. The performance reaches an averaged correct detection rate of 82.07% in case of two-class detection and three-class detection. To sum up, this paper provides a valuable method for the applications to avoid some traffic accidents caused by tired driving. SWA is combined with vehicle state information such as yaw angles and lateral positions, which can produce high recognition rate in simulation lab as shown in Qu's work [22]. Derived from this, it is expected to combine these types of information under real driving conditions to promote detection accuracy of driver fatigue levels in our future work. This allows additional useful information for driver fatigue level detection to be discovered.

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