Driving Distraction Analysis by ECG Signals: An Entropy Analysis

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Abstract. This paper presents a novel method in driving distraction analysis: entropy analysis of ECG signals. ECG signals were recorded continuously while 15 drivers were driving with a simulator. Mental computation task was employed as driving distraction. Sample entropy and power spectrum entropy of drivers. ECG signals while they were driving with and without distraction were derived. The result indicated that entropy of drivers ECG signals was sensitive to driving distraction and were potential significant metrics in driving distraction measurement.

Keywords: Entropy, Driving distraction, ECG signal.

1 Introduction

The increasing use of on-board electronics and in-vehicle information systems has made driving distraction a major concern in the driving safety field [1]. When drivers manage another task while driving, e.g. listening to the radio, holding a cell-phone conversation, employing on-board navigation system, the distraction of attention will decrease their performance, even causes traffic accident.

The analysis and recognition of driving distraction is significant to safety since it is the basis of avoiding distraction and the design of in-vehicle information system (IVIS) and other driving aided devices. Most of the studies focused on driving behavior and performance related to distraction. Eye movement and driving performance were investigated to analyze and identify the distraction in driving [2][3]. D'Orazioa et.al. established a visual framework to estimate the drivers' inattention while driving with secondary task [4]. Reaction Time on secondary task along with driving performance was recorded to explore driving distraction activity also [5].

Model for inferring psychological significance from physiological signals has been built since 20 years ago [6]. Physiological signals have been widely used in emotion recognition [7] [8] [9] [10]. However, to the limit of our knowledge, only a few study investigated drivers' functional state associated with driving workload by physiological indices. Jennifer, Healey and Rosalind monitored drivers' physiologic reactions during real-world driving situations using physiological sensors [11]. Electrocardiogram (ECG), Electromyogram (EMG), Electrodermal activation (EDA) and respiration were

P.L.P. Rau (Ed.): Internationalization, Design, HCII 2011, LNCS 6775, pp. 258–264, 2011.

recorded and were used to evaluate the stress of drivers in different driving task. Collet, Clarion and Morel et.al. evaluated the strain undergone by drivers when they managed the secondary task while driving. Electrodermal activity and instantaneous Heart Rate (HR) were recorded [12]. ECG is one of the widely used tools to explore cognitive requirements of complex task performance [13][14]. Most of the studies employed Heart Rate (HR) and Heart Rate Variability (HRV) to evaluate mental workload [11][12]. Few studies had explored the correlation between the original ECG signal and mental workload.

In the present research, we explored drivers' distraction by the original ECG signals through entropy analysis. In our experiments, drivers drove with and without secondary task respectively in a driving simulator. ECG signals were recorded while operation and performance data were recorded either. The ECG signals were analyzed in time domain and spectrum domain. Sample entropy can describe the complexity of a time series. Our hypothesis was that the complexity of the ECG signals of drivers with and without distraction would be different significantly. Therefore, we calculated the sample entropy in different time scales of the original ECG signals and compared the values in the two situations. Power spectrum entropy is often used in biomedical engineering, e.g. cerebral ischemia detection [15], sleep stages [16], myocardial infarction patients diagnosis [17]. In the present research, we derived the power spectrum entropy of the original ECG signals and tried to make it one of the metrics of drivers' distraction. The result indicated that the sample entropy and the power spectrum entropy of the original ECG signal were sensitive to driving distraction.

2 Material and Methods

2.1 Participants

The participants were 15 licensed drivers aged from 18 to 50 years (mean 25, SD 5.2). There were 7 males and 8 females. All the participants were healthy and not receiving medication. They gave their informed consent after having been informed about the main contents of the experiment and were paid for their participation.

2.2 Procedure

The experiment took place in a driving simulator. The driving environment was a one-way driving, three lanes highway scene in the simulated driving task. The driving task was car following. Drivers were required to follow the head car while it changed lanes, stepped on the accelerator or brake. They should operate the steering wheel, accelerator or brake of the simulator so that the following car can close to the head car as near as possible while avoiding collision. The management of the dual-task was made under driving conditions. The secondary task was double-digital addition mental computation. After 20 minutes exercises which made drivers familiar to the operation of driving simulator, the drivers performed the experiment included two sessions: driving without secondary task and driving with secondary task. The mental computation problems were presented to the drivers by a clear female voice through earphones while they were driving. Each problem was presented for 10 seconds. Participants spoke the result of their computation to the microphone. The number of mental computation problems was 60. Each session lasted 10 minutes.

2.3 Apparatus

The driving simulator consisted of two parts: first, simulated car operation device including control stick, accelerator and brake pedal. Second, driving behavior surveillance system based on computer consisted of driving task presentation, recording of driver's reaction, data management, feedback of driving state and alarming modules. ECG signal was recorded by KF2 dynamic multi-parametric physiological detector. This kind of wireless wearable physiological detector can record multiple physiological indices include ECG with 3 leads, respiration and body temperature. The data can be analyzed by a data processing software. Figure 1 shows the physiological detector and the driving simulator.

Fig. 1. The KF2 dynamic multi-parametric physiological detector and driving simulator

2.4 Data Collection

Driving performance and ECG data were collected. The driving performance data was recorded by the computer integrated with the simulator. Participants wore the physiological detector before the start of the experiments and began to record ECG signal until the end of the experiments. The ECG signal was sampled at the rate of 250 Hz.

3 Data Analysis

Physiological parameters were related to the Autonomic Nervous System (ANS) functioning. The ANS is known to give a close estimation of subjects' arousal especially through the orthosympathetic branch [18] specialized in mobilizing energy resources in response to internal and external milieu demands [19]**.** The energy resources needed in driving with and without secondary task should be different. Thus the physiological features should be different in the two situations. We derived sample entropy and power spectrum entropy of the original ECG signals in the two cases and tried to explore the effect of driving distraction in ECG signal. Original ECG signals were first denoised by discrete wavelet coif4. Sample entropy and power spectrum entropy were calculated consequently.

Sample Entropy is a statistic representing the self similarity of a time series [20]. The more complex the time series is, the larger the sample entropy is. In other words, the more self-similar the time series is, the fewer the sample entropy is. Fewer data is needed to derive robust estimation of sample entropy compared to some other statistics such as approximate entropy, kolmogorov entropy. Thus sample entropy is widely used in the study of experimental clinical cardiovascular and other biological time series. The calculation of sample entropy can be seen in [20]. Furthermore, on account of the multiple time scales inherent in healthy physiologic dynamics, Costa et.al. introduced multi-scale sample entropy [21]. We calculated the multi-scale entropy of the ECG signals in the two experiment sessions respectively. The scales lasted from 1 to 10.

Power Spectrum Entropy (PSE) is the entropy of the power spectrum of a time series. It describes uncertainty of the energy distribution of the time series in each frequency. The larger the PSE is, the more uniform the energy distribution is. The power spectrum entropy of the ECG signals in 6 frequency bands which corresponded to the main components of ECG signal were calculated.

4 Result

First, the multi-scale entropy of drivers with and without distraction are significant different. The univariate repeated measures F-test of the multi-scale entropy showed that significant levels in all the scales are less than 0.05 except for scale 1 ($F(1,14)=3.641$, $p=0.077$). Figure 2 describes the difference between the two cases. Sample entropy with distraction in each scale was larger than that without distraction which indicated that distraction would increase the complexity of ECG signal.

Table 1 is the PSE of the drivers' ECG signals with and without distraction. Line 4 and 5 are the result of univariate repeated measure which indicated the significant effect of distraction in the PSE of the critical bands of ECG signal.

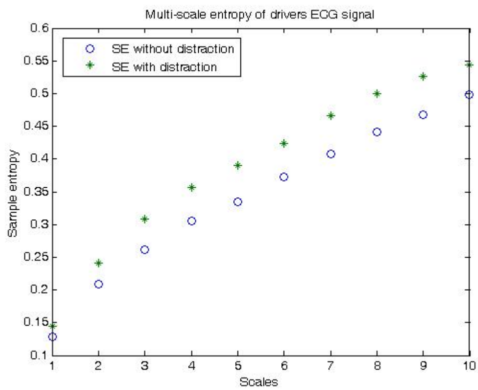

Fig. 2. Multi-scale entropy of drivers' ECG signal with and without distraction

Table 1. Power Spectrum Entropy of drivers' ECG signals

	Whole band	0~1.5Hz	0~4Hz	0~8Hz	0~20Hz
PSE_driving without distraction	4.0600(0.6283)	0.2332(0.1423)	0.5677(0.2934)	1.5585(0.7053)	3.5558(0.6945)
PSE_driving with distraction	4.1270(0.5965)	0.3169(0.2432)	0.6455(0.3528)	1.6213(0.7164)	3.6239(0.8727)
Univariant repeated measure	F(1,14)=4.5	F(1,14)=3.592	F(1,14)=3.913	F(1,14)=5.142	F(1,14)=5.694
p	0.052	0.079	0.068	0.040	0.032

The value of PSE in table 1 is mean and standard deviation (in the bracket) .

5 Discussion

Entropy analysis is a non-linear dynamic method. ECG signal is a kind of complex non-linear signal. Result of our experiments indicated that entropy analysis of ECG signal was meaningful to the analysis of drivers' functional state in driving distraction. Sample entropy can describe the complexity of a time series. Figure 2 showed that the sample entropy with distraction was larger than that without distraction. We tried to give a possible explanation that the distraction increased the mental workload which changed the functional state of the drivers. The change increased the complexity of the ECG signals. Similarly, we found that the power spectrum entropy of ECG signals which described the uncertainty of the energy distraction in spectrum domain was different in the two situations. The PSE in driving with distraction was larger than that in driving without distraction also. The results of the entropy in time domain and in spectrum domain are consistent.

6 Conclusion

The results of our experiment indicate that entropy analysis of ECG signals in driving is meaningful. The significant difference of entropy of driving with and without distraction shows that entropy of ECG signals is sensitive to driving distraction. This make entropy of ECG signals, either in time domain or in spectrum domain, be potential significant metrics in driving distraction measurement. Consequently, this implies that we can get benefit from the entropy of ECG signals in the recognition of driving distraction which is significant in some engineering psychology studies.

Acknowledgment. This work was supported by the 45"th Chinese postdocoral science foundation.

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