User Experience Quality Analysis Method Based on Frequency Domain Characteristics of Physiological Signal

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Abstract. In recent years, the development of intelligent driving is rapid, the related business is constantly upgrading, and the end-user service is becoming more and more perfect. From the perspective of end users, obtaining the evaluation results of experience quality is an effective way to enhance the core competitiveness of business. In this paper, the mapping method of user experience quality is established based on the frequency domain characteristics of SEMG signal, so as to obtain the current real experience quality of intelligent driving terminal users. Data analysis shows that this method can effectively obtain the quality of real user experience. This study can be used as reference data to improve the business experience of intelligent driving terminal users, improve the relevant technical parameters, and enhance the core competitiveness.

Keywords: Physiological signals · Frequency · Domain characteristics · QoE

1 Introduction

As a research hotspot in the field of intelligent transportation, vehicle network is a typical application of Internet of things technology in the field of transportation system [1, 2]. It is the only way for mobile Internet and Internet of things to develop into business essence and depth [3]. The Intelligent driving refers to the car and the car, car and road, cars and people, cars and sensing devices [4], such as interaction, realize vehicle dynamic system for mobile communications network communication with the public, including car and car, car and road, and sensing equipment through the established sensing technology and network communication technology for vehicle [5], road and environment information, and between cars and people, namely the human-computer interaction [6], how to realize the seamless docking is key to the current research [7, 8]. In the vehicle network environment, the quality of all sensor technology and network communication technology is measured by the experience quality of the driving user [9–11].

Emotion recognition is a research hotspot in artificial intelligence [12], human-computer interaction, pattern recognition and digital signal processing [13], as well as

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an important branch of emotion based computing [14]. In 1997, professor Picard of MIT media lab proposed that affective computing is one of the research methods for emotion [15]. Its purpose is to build a harmonious human-computer environment by giving computers the ability to recognize, understand, express and adapt to human emotions, and to make computers have higher and comprehensive intelligence. With the development of science and technology, people have higher and higher requirements for artificial intelligence, and how to make seamless communication between people and computers is also getting more and more attention [16–18]. As the basis of communication, emotion plays a more and more important role in human-computer interaction. Facial expression and voice emotion recognition systems will mature, however, both of these are non-physiological signals that do not directly reflect the inner psychological state of humans [18, 19]. Physiological signals (EMG, ECG, EGG) can more directly express people's current emotions. For example, EMG signal analysis can be used to judge the mental stress level and muscle fatigue state [20–24].

In the vehicle-net environment, the electromyographic signals of the driving user are easier to detect and can reflect the real experience quality of the driving user in real time. So this article uses the eight different emotional states (No emotion, Anger, Hate, Grief, Platonic love, Romantic love, Joy and Reverence) under electromyographic signal, and analyzes the relationship between their frequency characteristics and emotional state, in order to get through the electromyographic signal parameters to evaluate the quality of the vehicle under the network environment the user experience.

2 Related Work

Physiological signal refers to the signal spontaneously produced by human body in the physiological process, which contains a lot of information in human emotion and has great research significance. Physiological signals are regulated by the human nervous system and endocrine system, which can directly reflect the real emotions of human beings, and can greatly reduce the interference of other factors in the process of emotion recognition [25]. In the context of Intelligent driving, physiological signals change with the change of driving users' experience results of sensing technology and network communication technology, and the quality of user experience can be directly or indirectly reflected by the changes of human physiological signals [26]. By analyzing the relationship between driving user physiological signal characteristic parameters and user experience quality, we can regard the evaluation system as an open-loop system, taking human physiological signal changes as the input of the system and user experience quality as the output of the system [27]. The open-loop system can objectively represent the driving users' experience quality of various sensor technologies and network communication technologies of the Intelligent driving, so as to facilitate technicians to adjust relevant technical parameters in real time.

The electromyographic signal is the bioelectrical signal produced by the muscle activity and is the synthesis of the single action potential produced by the motor unit. SEMG signals are recorded from the skin surface and reflect the functional state of nerves and muscles. Because EMG signals can be recorded noninvasively, EMG signals have been used in a variety of fields, including motion analysis, neuromuscular system analysis, neuromuscular disease diagnosis, and prosthesis control. Because of SEMG signal can overcome the problems existing in the subjective psychological evaluation, quantitative analysis of the working load and muscle function status and high correlation exists between the indexes and subjective fatigue, so its in human computer interaction and ergonomics application has a unique advantage, for the improvement of man-machine environment provides a more objective and effective theory basis [28, 29].

In terms of human-computer interaction, facial expression and speech emotion recognition system [30, 31] is relatively mature. However, these methods are non physiological signals, which can not directly reflect the internal psychological state of human beings. Compared with facial images and speech, physiological signals can express people's emotions more directly [32–34]. For example, GSR (galvanic skin reaction) can be used to analyze and judge people's psychological stress level [33]. As the sum of muscle motor potential, SEMG can quantitatively determine the internal load state of human body and evaluate the muscle stress state. Since SEMG signal can be obtained noninvasively, SEMG signal has been used in many fields, including motion analysis, muscle system analysis, muscle disease diagnosis and prosthesis control. SEMG signal has a relatively mature analysis method and acquisition technology, which is suitable for the evaluation of user's forelimb muscle state. In order to obtain the user's psychological and emotional state, determine the quality of user experience, and improve the human-computer interaction environment [27, 36].

Studies show that when the human body for a long time in a less or more excited emotional psychological state, the system remains tense muscles, it will produce a certain amount of load, the load build-up can cause muscle changes in physical properties of excitability and conductivity and reduced contractility, muscle physical exhibition staying power and flexibility is abate, the muscle will not be able to produce, the force needed for this phenomenon is called muscle fatigue. When fatigue occurs, the conduction velocity of muscle fibers decreases, and local muscles will produce such sensations as soreness, numbness and weakness. Therefore, it is an effective experimental method to extract surface EMG signals and find out the frequency characteristic parameters reflecting the change of conduction velocity [37, 38].

3 Assessment Process and Data Analysis

The end user experience quality evaluation process based on SEMG is shown in Fig. 1.

As shown in the figure, physiological comfort index includes human body pressure distribution data and EMG signal data. According to the data characteristics of physiological signal indicators and five levels of comfort evaluation level, the evaluation data set $K = \{k_1, k_2, \cdots, k_n\}$ is defined by maximum value and minimum value method, As shown in formula (1):

$$z = \frac{\max(x) - \min(x)}{n} \tag{1}$$

Among them, $\max(x)$ and $\min(x)$ represent the maximum and minimum values of a class of physiological data, $n \sim x_{ij}$ values are graded, and $z \sim n$ values are the mean difference between the grades. In this paper, trapezoidal fuzzy method is used to reflect

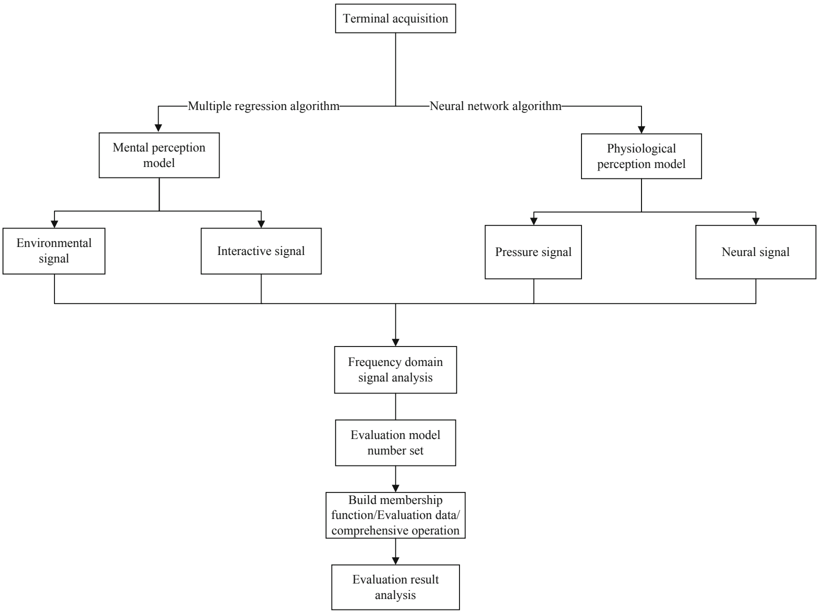

Fig. 1. Assessment process.

the subjectivity of the end-users, and the correlation between the evaluation indexes and the evaluation data set is studied. As shown in formula (2).

$$\alpha_{ij} = \begin{cases} \frac{x-\alpha_{ij}^{L}}{\alpha_{ij}^{ML}-\alpha_{ij}^{L}}, x \in \left(\alpha_{ij}^{L}, \alpha_{ij}^{ML}\right) \\ 1, x \in (\alpha_{ij}^{ML}, \alpha_{ij}^{MR}) \\ \frac{x-\alpha_{ij}^{R}}{\alpha_{ij}^{MR}-\alpha_{ij}^{R}}, x \in \left(\alpha_{ij}^{MR}, \alpha_{ij}^{R}\right) \\ 0, x \in \left(-\infty, \alpha_{ij}^{L}\right) \cup \left(\alpha_{ij}^{R}, 0\right) \end{cases} \tag{2}$$

Among them, a_{ij} is the membership degree of the u_{ij} index to the evaluation set $K = \{k_1, k_2, \cdots, k_n\}$, $\alpha_{ij}^{L}, \alpha_{ij}^{ML}, \alpha_{ij}^{MR}, \alpha_{ij}^{R}$ is the coordinate value of the trapezoidal membership function respectively, and there is $\alpha_{ij}^{L} < \alpha_{ij}^{ML} < \alpha_{ij}^{MR} < \alpha_{ij}^{R}$. If $\alpha_{ij}^{L} < \alpha_{ij}^{ML} = \alpha_{ij}^{MR} < \alpha_{ij}^{R}$, the trapezoidal membership function is transformed into a triangular membership function.

The experimental results show that the conduction velocity of muscle fibers is directly related to local muscle fatigue. Surface emg signals are extracted and converted into frequency characteristic parameters that can reflect the change of conduction velocity, thus reflecting the fatigue degree of muscles. These characteristic parameters are mainly obtained through time-domain and frequency-domain analysis.

In frequency domain analysis, the main analysis method is to conduct fast Fourier transform on EMG signal to obtain the spectrum or power spectrum of EMG signal, which can reflect the changes of EMG signal in different frequency components, so it can better reflect the changes of EMG signal in frequency dimension. The spectral shift of SEMG signal power spectrum can be used as an experimental indicator of the conduction velocity of muscle fibers.

In order to quantitatively characterize the spectrum or Power spectrum of SEMG signals, researchers often use the following two indicators, namely Mean Power Frequency (MPF) and Median Frequency (MF).

The calculation method distribution of MPF value and MF value is as follows:

$$\mathrm{MPF} = \int_0^{\infty} \mathrm{fP(f)df} \Bigg/ \int_0^{\infty} \mathrm{P(f)df} \tag{3}$$

$$\int_0^{\mathrm{MF}} \mathrm{P(f)df} = \int_{\mathrm{MF}}^{\infty} \mathrm{P(f)df} = \frac{1}{2}\int_0^{\infty} \mathrm{P(f)df} \tag{4}$$

Where $P(f)$ is the EMG power spectrum.

Because the average power frequency is highly sensitive to the frequency spectrum variation under low load conditions, it can be used as the reliability measurement parameter of local muscle fatigue in human body. This experiment mainly detects the change of SEMG signal spectrum under different psychological and emotional states of users. There is no obvious muscle activity. However, due to the long-term load accumulation process, frequency-domain parameters are adopted for analysis.

4 The Experimental Results

In this paper, the emotional physiology database of MIT was used as the source data for processing and analysis. According to the data processing results, the upper extremity SEMG signals corresponding to different experience quality of users in the actual vehicle network environment under driving conditions were collected in subsequent studies.

The MIT emotion physiology database is 32 physiological data sets per day for 20 consecutive days. The DataSet I consists of four physiological signals and eight emotional state measurements. The experimenter sat in a quiet space at the same time every day and tried to experience eight emotional states under the guidance of the computer prompt system, and recorded the physiological signals of the experimenter in real time. The sampling frequency of all data was 20 Hz and the sampling time was 100 s. Participants were asked to experience eight emotional states: No emotion, Anger, Hate, Grief, Platonic love, Romantic love, Joy and Reverence.

The average power frequency (MPF) of SEMG signals in eight different emotional states of the subjects within 20 days was calculated and plotted as the corresponding histogram, as shown in Fig. 2. Since the experimental data are 2000 data of subjects in different emotional states, the duration of each emotion cannot be controlled absolutely, so the 2000 data in the data set may be intercepted at the beginning or end of the emotion. We took the average value of the 20-day measurement data and observed the mean value of MPF value of the experimenter's SEMG signal under different emotions, as shown in Fig. 3.

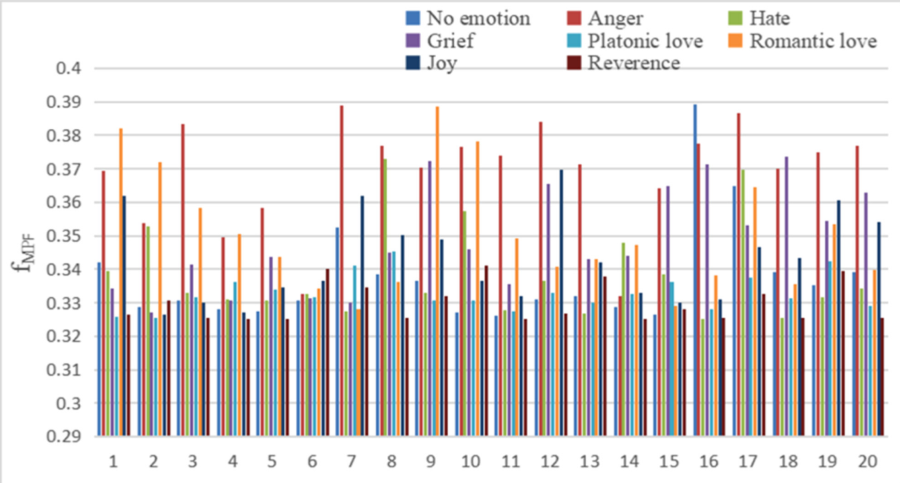

Fig. 2. Histogram of MPF value of SEMG signal in eight states.

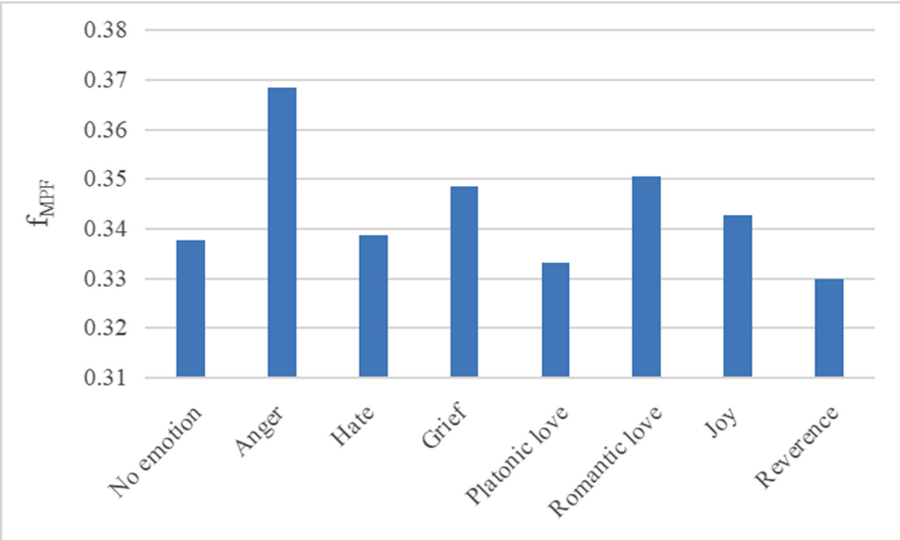

Fig. 3. Mean MPF value of SEMG signal in 8 states within 20 days.

According to the results in Fig. 1 and Fig. 3, under Anger, Grief, Romantic love and Joy, SEMG signal MPF value had a larger amplitude, It indicates that the conduction velocity of muscle fibers is faster. The MPF value of SEMG signal was smaller under Platonic love, emotion and No emotion, and the results indicate that the conduction velocity of muscle fibers is slow.

Previous studies showed that the average power frequency MPF decreased with the gradual fatigue of muscles under static load. This experimental data for the subjects did not appear under the muscle fatigue of acquisition, and no obvious passive fatigue phenomenon, thus the experimental results show that if the experimenter long-term at our Romantic love, Joy, Anger, Grief and four kinds of emotion, the muscular system will continue to be nervous, reduce muscle fiber conduction velocity and muscle fatigue state, the decrease of the quality of the user experience. If the subjects were in the three emotions of Platonic love, emotion and No emotion for a long time, the muscle system was relatively relaxed, and the excitability, conductivity and contractibility were less affected by the time dimension, which would not change significantly. The subjects were not prone to obvious fatigue, indicating that the user experience quality was good.

Figure 4 shows the spectrum of SEMG signals in eight emotional and psychological states of the subjects during the test on a certain day. The SEMG signal spectrum diagram showed that the frequency spectrum amplitude of the subject was larger in Anger and Romantic love, and the high and low frequency parts were significantly increased,

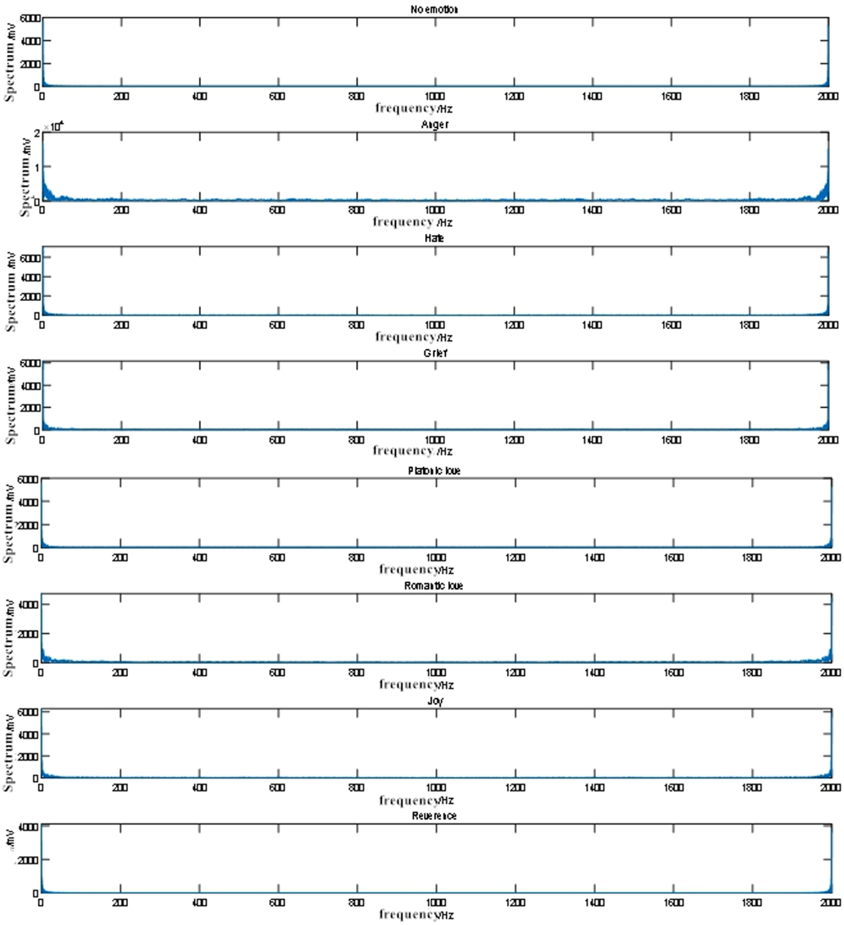

Fig. 4. SEMG spectrum diagram.

indicating that the muscle system of the subject was prone to fatigue in a certain period of time under these two emotions. Under emotion and No emotion, the amplitude of SEMG signal spectrum was small, and the distribution of high and low frequency was less, indicating that the muscle system of the subjects was not prone to fatigue in a certain period of time under these two emotions, and the quality of user experience was better than other psychological and emotional states.

Experiment found that the short-time Fourier transform of MPF, to some extent can well represent changes of muscle fatigue, but because of the Fourier transform is only applicable to smooth the mutations in the signal, so when change the SEMG signal, based on Fourier transform of frequency domain feature is not difficult to fully reflect the changes of muscle fatigue. Due to the experimental data for the subjects in the corresponding part of the SEMG signal with emotional state, likely in the mood or end the beginning of the end, there may be a jump, the results can only qualitative analysis to get the user psychological emotional state and there were some correlation between physiological signal characteristic parameters, can be used to get the user experience as a quality reference data. Later research can obtain corresponding user SEMG signals by changing various technical parameters in the Intelligent driving environment, and use more characteristic parameters to represent the user experience quality under different technical parameters, so as to provide guiding data for a more harmonious human-computer interaction environment.

5 Conclusion

In this paper, the mapping method of user experience quality is established based on the frequency domain characteristics of SEMG signal, so as to obtain the current real experience quality of intelligent driving terminal users. Data analysis shows that this method can effectively obtain the quality of real user experience. The relationship between MPF, the characteristic parameter of SEMG signal in frequency domain of No emotion, Anger, Hate, Grief, Platonic love, Romantic love, Joy and mood state of subjects was analyzed to provide reference data for judging the quality of user experience. The experimental results showed that in the state of Anger, Hate and other psychological mood swings, users had a large MPF amplitude and a large frequency spectrum in the low and high frequency bands, indicating that in this emotional state, the muscle system would be continuously tense, resulting in decreased muscle fiber conduction velocity, relatively easy muscle fatigue and decreased user experience quality. When users experience less disturbance of emotion such as agitation and No emotion, the muscle system is relatively relaxed, the excitability, conductivity and contractility are less affected by time dimension, and No significant change will occur. Users are not prone to obvious fatigue, indicating that the user experience quality is good.

The research results of this paper show that SEMG signals can be used as physiological signals to directly obtain user experience quality in the context of the Intelligent driving, and the characteristic parameters of user SEMG signals can be acquired in real time. The influence of technical parameters of the Intelligent driving on user experience quality can be analyzed, so as to create a more harmonious and integrated human-computer interaction environment.

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