Research on User Experience Quality Evaluation Method of Internet of Vehicles Based on sEMG Signal

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Abstract. In recent years, with the rapid development of Internet of vehicles, service providers and operators need to constantly upgrade and optimize their related services (communication nodes, terminal driving safety monitoring, intelligent vehicle), and the evaluation of end-user experience quality is the core of improving business. From the above point of view, this paper proposes an effective method to evaluate the psychological perception of end users by using the SEMG (Surface electromyograph) of end users. The method uses time domain features to represent the changing trend of users in different emotional states, and maps the relationship between psychological perception, so as to effectively evaluate the experience quality of end users. The results show that the method can adapt to the evaluation of experience quality of end users in the Internet of vehicles, obtain the psychological experience quality of current users, and provide strong support for service providers and operators to improve their core business of vehicle network.

Keywords: SEMG · RMG · The Internet of vehicles · QoE

1 Introduction

The Internet of things is regarded as the third wave of the world information industry after the computer Internet and mobile communication [1–3]. The application of the Internet of things in the field of intelligent transportation, namely the Internet of vehicles, has a very broad prospect and a high technical and economic feasibility. The Internet of vehicles is a concentrated embodiment of the application of the Internet of things technology in the field of intelligent transportation, and also a key area where the Internet of things technology has great potential [4–7]. The Internet of vehicles is expected to completely solve some existing traffic problems, such as traffic accidents, traffic congestion, etc. Internet of vehicles is a new application technology [6]. How to achieve high quality human-computer interaction in the vehicle network environment, that is to achieve seamless communication between people and vehicles, has attracted more and more attention [8]. Human physiological electrical signals are the direct response

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of human behavioral consciousness and sensory experience. By extracting certain characteristics of human physiological signals, the recognition of human emotional state can be used as an effective bridge to realize seamless human-computer interaction [9–11]. Emotion recognition can remove the barriers between people and vehicles, make human-computer interaction more harmonious, and effectively improve the quality of human-computer interaction and user experience in the context of the Internet of vehicles [12–14]. Emotion recognition is the behavior that the computer analyzes and processes the signal collected from the sensor to obtain the psychological and emotional state the user is in. From the point of view of physiological psychology, emotional state is a kind of compound state of organism, which involves both experience and physiological reaction as well as behavior [15]. Its composition includes at least three factors: emotional experience, emotional expression and emotional physiology. At present, there are two ways for emotion recognition. One is to detect physiological signals such as respiration, heart rate and body temperature, and the other is to detect emotional behaviors such as facial feature expression recognition, voice emotion recognition and posture recognition. Among them, facial expression and speech emotion recognition system is relatively mature [16]. However, both of these methods are non-physiological signals and cannot directly reflect the inner psychological state of humans. Compared with facial images and speech sounds, physiological signals can express people's emotions more directly [17]. For example, GSR (galvanic skin response) can be used to analyze and judge people's mental stress level [18]. Surface electromyograph (SEMG), as the sum of the muscle motor potential, can quantitatively determine the internal load state of human muscles and evaluate the muscle stress state. Because sEMG signals can be obtained non-invasively, sEMG signals have been used in many fields, including motion analysis, muscle system analysis, muscle disease diagnosis and prosthesis control. SEMG signal has relatively mature analysis methods and acquisition technology, which is suitable for evaluating the user's forelimb muscle state in the on-board environment, so as to obtain the user's psychological and emotional state, determine the quality of user experience, and improve the human-computer interaction environment [19].

In view of this, from the perspective of end-user experience quality, this paper proposes an evaluation method of end-user experience quality based on the characteristics of SEMG. The mapping system is constructed by using the time-domain characteristics, and the parameters of user's psychological and emotional state are collected to evaluate the change trend of physiological signals in different emotional states, so as to obtain the end-user experience quality, and provide strong support for their core business and operators.

2 Related Work

In the context of Internet of vehicles, users' physiological signals show certain regularity as the quality of user experience changes. The quality of user experience can be directly or indirectly reflected by the changes in the characteristic parameters of human physiological signals. By analyzing the relationship between user physiological signal characteristic parameters and user experience quality, we can regard the evaluation system as an open-loop system, taking human physiological signal characteristic parameters as the input of the system and user experience quality as the output of the system, as shown in Fig. 1 [20, 21].

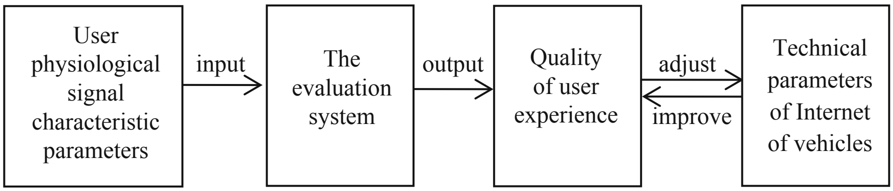

Fig. 1. User experience quality open-loop evaluation system.

In the Internet of vehicles environment, the quality evaluation standard of network protocol design and measurement is the quality of user experience. The preliminary study of our team shows that the differences in network protocols and communication capacity in the vehicle network environment can lead to different quality of user experience [22–25]. In order to improve the quality of user experience as the ultimate design goal, this paper intends to start with human physiological signals and studies the relationship between human physiological signals and users' emotional state, so as to further adjust the parameters such as network protocol or communication mode in real time through human physiological signals in the later research, and achieve the optimal user experience state [26, 27]. Human physiological signal contains a lot of information in human emotion, which is of great research significance. Physiological signals are modulated by the person's nervous system and endocrine system, and can directly reflect the true feelings of mankind, and the emotional signal associated with physiological signal process can largely reduce the interference of other factors [28, 29]. Therefore, the preliminary establishment of the relationship between users' physiological signals and their emotional states is conducive to the design of various parameters in the later Internet of vehicles environment.

The team's research on the technical parameters of the network architecture of the Internet of vehicles shows that the ultimate goal of the design of the technical parameters of the vehicle network is to achieve a higher quality of user experience. According to the quality of user experience represented by physiological signal parameters, it is more targeted to adjust and improve various technical parameters of the Internet of vehicles. SEMG signal is a comprehensive superposition of the action potential generated by the excitation of multiple motor units in the muscle at the detection electrode, which can be obtained by non-invasive measurement. In the field of biomedicine, the peak value of muscle potential in surface electromyography is often used as an indicator to evaluate the degree of muscle contraction [30–33]. The peak value is considered to be the most direct indicator to observe the degree of muscle activity. Experiments have proved that the conduction velocity of muscle fibers is directly related to the state of local muscles, and the characteristic parameters of sEMG signal can reflect the conduction velocity of muscle fibers and the state of muscle load. The characteristic parameters of sEMG signal are mainly obtained through time domain and frequency domain analysis. The time domain characteristic is a function of time, which is used to describe the amplitude characteristics of time series signal, and the time domain characteristic value is easy to extract and stable. In the experiment, the characteristic parameters of sEMG signals under different emotional states were extracted and analyzed in the time domain [34, 35].

Root mean square (RMS) is the most reliable characteristic parameter in time domain analysis, and is a traditional method to characterize EMG signals [25, 36]. RMS describe the average variation characteristics of sEMG signals over a period of time, showing a significant correlation with muscle tone, reflecting muscle activity, and is used to detect muscle motor unit recruitment and the size of action potential. RMS is defined as the square root of the sum of squares of all data points divided by the number of data points, which is defined as:

$$\mathrm{RMS} = \sqrt{1/\mathrm{T} \int_{\mathrm{t}}^{\mathrm{t+T}} \mathrm{sEMG}^2(\mathrm{t})\mathrm{dt}} \tag{1}$$

Where, T is the observation time length of sEMG signal.

Relevant studies have shown that the RMS of sEMG signals are in direct proportion to muscle tension, which is the basis for maintaining different positions and normal movements of the body [37, 38]. The greater the muscle tension, the more likely the user is to feel tired, and the less comfortable the human body is. The smaller the muscle tension, the better the comfort of the human body.

3 Assessment Process

The end user experience quality evaluation process based on sEMG is shown in Fig. 2.

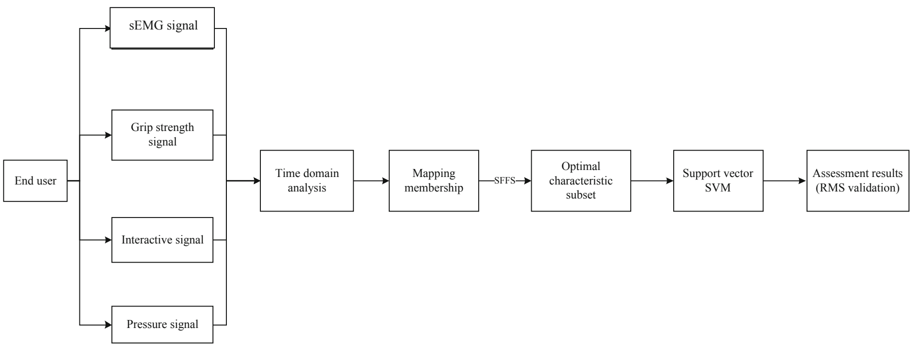

Fig. 2. Assessment process.

As shown in the figure, the preprocessing terminal user obtains the parameters and establishes sEMG signal $\mathrm{p}(t)$, grip strength signal $\mathrm{q}(t)$, interaction signal $\mathrm{r}(t)$ and pressure signal $\mathrm{s}(t)$.The characteristics of grip strength signal are time-domain and time-frequency-domain features. The mean value $\overline{\mathrm{y}}$, variance $\mathrm{Var}(\overline{y})$, maximum value $\max(y)$ and minimum value $\min(y)$ of the signal are extracted in time domain. The square sum $\mathrm{m_i}$

of wavelet coefficients in layer I, the proportion of positive coefficients in wavelet coefficients mr_i, and the logarithm of the ratio of the sum of positive coefficients and the absolute sum of negative coefficients in wavelet coefficients are extracted in time-frequency domain.

The characteristic of the interaction signal is the duration t of the abnormal shift center pressure point, and the characteristic of the pressure signal is the absolute mean value. The dimension of different terminal parameters is different, and there is a big difference in the order of magnitude. When solving the optimal classification surface, the feature parameters with small order of magnitude will be dominated by the feature parameters with large order of magnitude, which weakens the feature parameters of small order of magnitude. Therefore, it is necessary to unify the magnitude of feature parameters to eliminate the differences. The formula (2) is used.

$$y_i' = \frac{2y_i - y_{\max} - y_{\min}}{y_{\max} - y_{\min}}, i = 1, 2, \cdots n \tag{2}$$

Where y_i is the original feature parameter component, y_i' is the normalized feature parameter component, and its range is between -1 and $+ 1$; y_{max} and y_{min} are the maximum and minimum values of the original feature parameters in the training samples, and N is the total number of training samples). Taking the optimal feature subset as the input of support vector machine, the features in the feature set are filtered based on SFFS selection and elimination criteria, and the criterion function (3) is established:

$$\max_Y G(Y) = \frac{n_Y}{N_Y}, Y \in X \tag{3}$$

Where x is the complete set of fatigue characteristic parameters, y is the non empty subset of X, G (y) is the criterion function, that is, the detection accuracy rate of fatigue detection model, N_Y is the number of test samples, and n_Y is the number of samples correctly identified in the test samples. From the end-user state parameters as the output, the experience quality evaluation model is constructed, and the differences are compared by using the results of mean square deviation analysis.

4 Data Processing and Analysis

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 100s. Participants were asked to experience eight emotional states: No emotion, Anger, Hate, Grief, Platonic love, Romantic love, Joy and Reverence.

The root mean square value (RMS) of the sEMG signal of the subjects in 8 different emotional states within 20 days was calculated and plotted as a change curve, as shown in Fig. 3.

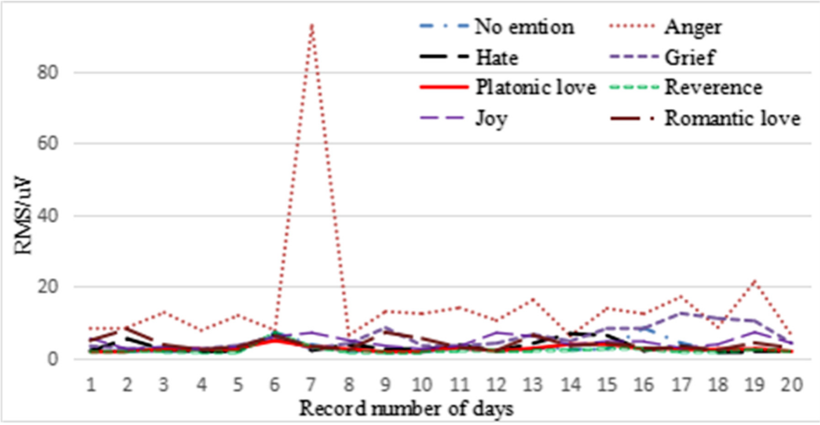

Fig. 3. The variation curve of RMS under eight emotions.

As can be seen from Fig. 3, the RMS value of sEMG signal varied greatly under Anger, Grief and Joy, indicating that the physiological signal of the experimenter was highly sensitive to the three emotions and was prone to fluctuations. Under Platonic love, Reverence, and No emotion, RMS of sEMG signal changed less, indicating that physiological signals of the subjects were less sensitive to the three emotions.

In this paper, RMS values of sEMG signals in eight emotional states during the 20-day test were comprehensively drawn into a three-dimensional diagram, as shown in Fig. 4. Figure 4 can comprehensively reflect the relationship between RMS value of sEMG signal, test time and users' emotional state. When the user enters a set emotional state for a certain period of time, a series of original emg signals will be generated to change with the emotional state. The three-dimensional diagram of the change of RMS value of sEMG signal characteristic value with the test time and the user's emotional state showed that, during the specific test time, the user's RMS value in Anger, Grief, Romantic Love and Joy emotional state was large, and the user's RMS value in the four states fluctuated greatly with the test time, indicating that the user's overall muscle load was large and it was easy to enter the fatigue state. In the state of No emotion, emotion and Platonic love, the sMEG signal characteristic value RMS amplitude is small, and the fluctuation is small in different test time, that is, the user's overall muscle load is small.

Figure 4 can reflect the changing relationship between the time-domain characteristic value RMS of user sEMG signal and the test time and the user's emotional state as a whole. The RMS amplitude of the EMG signal is averaged under eight emotional states during the 20-day test, which can reflect the relationship between the user's muscle load intensity and emotional state as a whole. At the same time, since the experimental data are 2000 data of subjects in different emotional states, the duration of each emotion

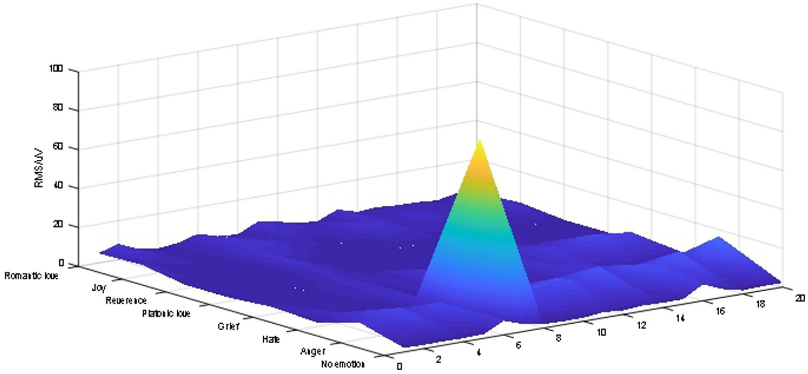

Fig. 4. The three-dimensional figure of RMS.

cannot be controlled absolutely, so the 2000 data in the data set may be intercepted at the beginning or end of the emotion. The daily test data do not fully reflect the changing trend of users' sEMG signals with their emotional states.We took the average value of the time-domain characteristic value RMS of sEMG signal for the experimenter in each emotional state for 20 days, and observed the overall change trend of the characteristic value RMS of sEMG signal for the experimenter under different emotions, as shown in Fig. 5.

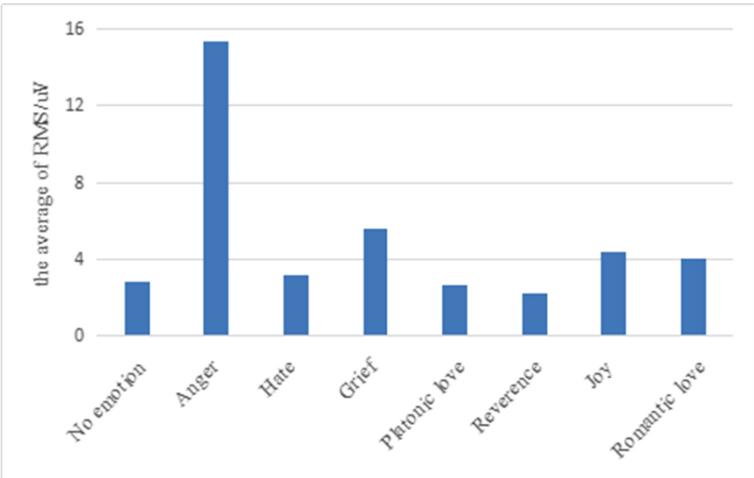

Fig. 5. Mean value of RMS under different emotions.

As can be seen from the results in Fig. 5, compared with other emotional states, the mean value of sEMG signal RMS was larger under Anger, Grief and Joy, indicating that the muscle tension of the subjects was larger under the corresponding emotional state, and it was easier to reach the fatigue state. However, the mean value of RMS of sEMG signal was lower under Platonic love, Reverence, and No emotion indicating that the muscle tone of the experimenter was lower and the comfort level was higher.

Data analysis results show that the user's physiological signal and there were some correlations between the emotional state, so in the networked environment, when the sensor technology, network communication technology, and other parameters of the corresponding change, user experience quality change, then lead to involuntary change user's physiological signal sEMG signal, and the trend of change trend in normal human cognition. In the context of the Internet of vehicles, the quality of user experience can be obtained through real-time detection of users' physiological signals, so as to make corresponding adjustments to various technical parameters of the Internet of vehicles and achieve seamless human-machine interaction.

5 Conclusion

In recent years, with the rapid development of vehicle Internet, service providers and operators need to constantly upgrade and optimize their related services (communication nodes, terminal driven security monitoring, intelligent vehicles) and end-user experience quality evaluation is the core of improving business level. From the above point of view, this paper proposes an effective method to evaluate the psychological perception of end users by sEMG (surface electromyography). This method uses time domain features to represent the changing trend and emotional state of different users, and maps the relationship between psychological perception, so as to effectively evaluate the experience quality of end users. The results show that the method can adapt to EVA to evaluate the experience quality of vehicle Internet end users, obtain the psychological experience quality of current users, provide strong support for service providers and operators, and improve their vehicle network core business.

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