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Research Article

A Braking Intention Identification Method Based on Data Mining for Electric Vehicles

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A braking intention identification method based on empirical mode decomposition (EMD) algorithm and entropy theory for electric vehicles is proposed. EMD algorithm is given to decompose nonstationary brake pedal signal to stationary intrinsic mode function (IMF), which is the base of data mining. After that, entropy theory is used to extract brake pedal signal features. A braking intention identification model is built based on fuzzy c-means clustering algorithm. The hardware and software for braking intention identification system based on this method is set up to do offline and real-time experiments. The results show that the identification method proposed in this paper has good real-time quality and can distinguish moderate braking intention and gentle braking intention better.

1. Introduction

1.1. Motivations and Technical Challenges. The problem of environmental pollution and energy shortage has prompted the development of electric vehicles. However, electric vehicles have a short-extended mileage, which hinders the development of electric vehicles. Therefore, it is imperative to improve the efficiency of electric energy utilization, which can extend electric vehicles' mileage [1–3].

Regenerative braking is one of the key technologies for electric vehicle to improve the efficiency of energy utilization, which increases the extended mileage [4, 5]. In order to ensure the safety and reliability of the braking process, the electric vehicle must retain the traditional mechanical friction braking system. That means an electric vehicle has a hybrid braking system with both regenerative braking system and traditional mechanical friction braking system. Therefore, a control strategy is needed to determine how regenerative braking system and mechanical friction braking system work coordinately. The principle of control strategy is that when the driver brakes gently, regenerative braking has priority to work to recover braking energy as much as possible. With the increase of the braking urgency, mechanical friction braking gets involved gradually. In emergency braking process, only mechanical brake works to ensure the safety and reliability of the braking process [6–10].

Consequently, braking control strategy of an electric vehicle is based on the driver's braking intention. Whether the identification result of driver's braking intention is correct has a direct impact on the rate of energy recovery during regenerative braking. Therefore, how to identify the driver's braking intention accurately is an important scientific problem to be solved for regenerative braking technology of electric vehicles.

1.2. Literature Review. Japan's national transportation safety and environment laboratory and Toyota corporation have worked together to study the characteristics of brake pedal force and brake pedal displacement to determine the threshold of braking intention recognition parameters to identify the driver's braking intention, which can distinguish between the general braking intention and emergency braking intention [11]. Mercedes-Benz corporation identified the driver' intention by the change rate of the brake pedal displacement [12]. Bosch applies braking intention identification to the development of emergency brake assist systems. When the brake pedal manipulating speed is higher than the threshold, the system will recognize the driver's emergency braking requirements and build up the braking force in a faster way to help the vehicle to stop quickly [13]. Zhang et al. [14] use statistics of fifteen sets of data from different drivers to

evaluate the threshold value of emergency braking intention for electronic braking system (EBS). In [15], TS-fuzzy system was built to identify driver's normal braking and emergency braking intention, which adopts pedal stroke and the change rate of the pedal stroke as identification parameters. Yang et al. [16] used unsupervised machine learning algorithms, such as K-means and Gaussian mixture model (GMM), to identify driver's braking intention. Duy Tran et al. [17] proposed an approach to predicting driver's intentions using hidden Markov model (HMM). In [18], eye fixation and brake pedal position were used to identify emergency braking. In [19], a layering hidden Markov model and adaptive neurofuzzy inference system for braking intention identification were built to optimize AMT shift control strategy to improve the braking energy recovery rate of the extended-range heavy commercial electric vehicle. In [20], a new regenerative braking control strategy based on braking intention identification and motor working characteristics is proposed. In the paper, braking intention is classified as the emergency braking and the normal braking. Model predictive control is used to achieve different braking intentions to make braking performance better. In [15], the braking torque distribution strategy is proposed based on the road conditions and driver's braking intentions for electric vehicles. Driver's braking intentions are classified as the emergency braking and the normal braking, which were identified by TS-fuzzy system. The inputs of the fuzzy system are braking pedal travel and the change rate of the pedal travel. The output is driver's braking intention. In [21], to improve braking intention identification accuracy, a braking intention identification method based on the Gaussian mixture-hidden Markov model and generalized growing and pruning radial basis function neural network is proposed. Driver's braking intentions are classified as the slight braking, the normal braking, and the emergency braking. Brake pedal displacement, brake pedal speed, brake pedal force, and vehicle speed are used to identify braking intentions. In [22], a regenerative braking control strategy based on braking intention is proposed. The regenerative braking control strategy is developed based on four braking intentions, which are emergency brake, heavy brake, moderate brake, and slight brake, to decide which brake modes to choose. HMM and EM algorithm are used to identify brake intentions. In both [23, 24], the control system is based on driver's intention identification for electric vehicles to distribute torque according to driver's torque demand, which is amended by driving and braking intentions. The driver's intentions are identified by fuzzy logic threshold identification.

1.3. Original Contributions and Outline of the Paper. Drivers of different driving styles operate braking pedal with distinguishable travels, for different braking intentions, for instance, gentle braking, moderate braking, and emergency braking. Therefore, braking pedal travel reflects emergency level of braking intentions. Braking pedal travel can be measured by displacement sensor, which transforms displacement to voltage signal. But sometimes in time domain, features of the braking pedal travel's voltage signal of gentle braking and moderate braking are not obvious.

So, in this paper, a braking intention identification method for electric vehicles is proposed based on EMD and entropy theory. First, the brake pedal travel's voltage signal data of different braking intentions were further mined based on EMD to obtain the IMFs of brake pedal travel's voltage signals, which cannot extract the features directly. Second, the IMF's sample entropy of brake pedal travel's voltage signal was computed, and the IMF's sample entropy of brake pedal signals is the features of brake pedal signals for different braking intentions. The Shannon entropy is used to choose which IMFs' sample entropies can be used as the features of the brake pedal travel signal. IMFs' sample entropies which were chosen are the feature vector of the brake pedal travel signal. Finally, the feature vectors of the brake pedal travel signal of different braking intentions were clustered by clustering algorithm, which means braking intentions were identified.

2. Principle and Algorithm of EMD

Brake pedal signal is nonstationary data signal. So, the features of brake pedal signal obtained by using entropy theory directly may lose its original physical significance. Therefore, the brake pedal signal should be processed by empirical mode decomposition (EMD) before feature extraction, which can decompose the signal into Intrinsic Mode Functions (IMF).

EMD algorithm is shown as follows.

First, all extreme points of the initial signal $X(t)$ are found out; then cubic spline interpolation should be done for all maximum and minimum value points, respectively. After that, upper envelope $X_{\max}(t)$ and lower envelope $X_{\min}(t)$ of the initial signal are given by numerical fitting. $m_1(t)$ is the mean value of $X_{\max}(t)$ and $X_{\min}(t)$

$$m_1(t) = \frac{[X_{\max}(t) + X_{\min}(t)]}{2} \tag{1}$$

$h_1(t)$ is obtained by initial signal subtracting of the mean of the envelopes

$$h_1(t) = X(t) - m_1(t) \tag{2}$$

$h_1(t)$ serves as a new initial signal and repeat above steps if $h_1(t)$ is not an IMF

$$h_{11}(t) = h_1(t) - m_{11}(t) \tag{3}$$

where $m_{11}(t)$ is the mean value of $h_1(t)$'s envelopes. The algorithm above will be repeated k times if $h_1(t)$ is still not an IMF; then $h_{1k}(t)$ is given

$$h_{1k}(t) = h_{1(k-1)}(t) - m_{1k}(t) \tag{4}$$

The termination criterion for $h_{1k}(t)$ selection procedure is given below

$$SD = \sum_{t=0}^{T} \left| \frac{\left|h_{1(k-1)}(t) - h_{1k}(t)\right|^2}{h_{1(k-1)}^2(t)} \right| \tag{5}$$

where SD is the standard deviation of two adjacent processing results, and its value should be appropriate. If SD is

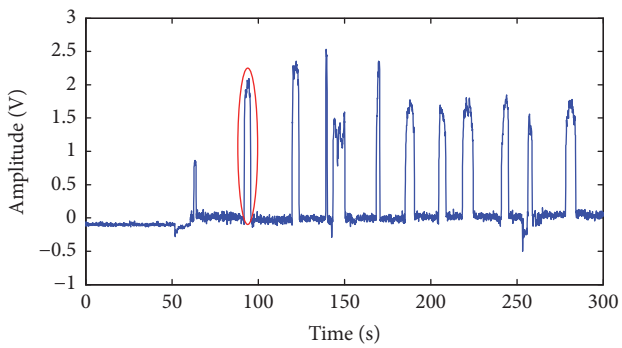

Figure 1: Brake pedal signal during moderate braking.

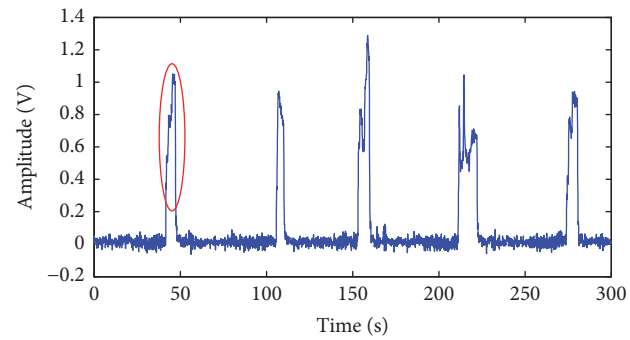

Figure 2: Brake pedal signal during gentle braking.

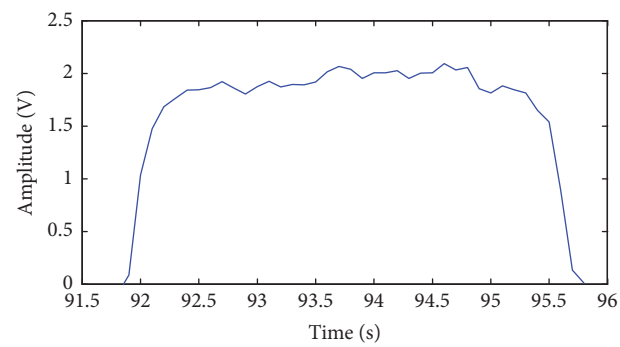

Figure 3: Chosen data in moderate braking process.

too small, IMF will become frequency modulated signal with constant amplitude which has no features. If SD is too large, the terminating condition will be too loose, which makes screening results not able to be IMFs. Experience has shown that SD should be 0.2 to 0.3 to guarantee that an IMF is linear and has stable physical features.

$h_{1k}(t)$ is the first-order IMF which is $c_1(t)$ in equation (6), if $h_{1k}(t)$ in equation (4) satisfies the requirements of the termination criterion. Residual signal $r_1(t)$ as shown in (6) is obtained by initial signal $X(t)$ minus the first-order IMF

$$r_1(t) = X(t) - c_1(t) \tag{6}$$

Repeat EMD procedure above; all of residual signals $r_i(t)$ can be figured out by iterative procedure as shown in

$$r_{i-1}(t) - c_i(t) = r_i(t) \quad i = 1, 2, 3, \cdots, n \tag{7}$$

EMD procedure is terminated when residual signal $r_i(t)$ is a monotonic function which means it is impossible to extract IMF anymore. Consequently, initial signal $X(t)$ consists of nth order IMF and the residual signals $r_n(t)$, as shown in

$$X(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \tag{8}$$

The experimental data of brake pedal signal of moderate braking and gentle braking are shown in Figures 1 and 2. Experimental data as marked by the red circle in Figures 1 and 2 are chosen to be processed by empirical mode decomposition. The experimental data chosen are shown in Figures 3 and 4.

The two segments of brake pedal signals are transformed into IMFs by EMD algorithm, which are shown in Figures 5 and 6. As depicted in Figures 5 and 6, the features of the brake pedal signal IMFs of moderate braking and gentle braking are different obviously. Therefore, the two braking modes can be identified by using appropriate algorithm to extract signal feature.

3. Feature Extraction and Clustering Recognition

3.1. The Principle of Sample Entropy. The complexity of the signal time series is reflected by sample entropy. The more complex the signal time series is, the greater the sample entropy is, while the simpler the signal time series is, the smaller the sample entropy is. Brake pedal signals' IMF's sample entropy of gentle braking and moderate braking was computed. The IMF's sample entropy of each braking intention's brake pedal signal is the features of brake pedal signals for different braking intentions.

The calculation method of sample entropy is as follows:

(1) m-dimension vector $X(i)$ is constructed,

$$X(i) = [x(i), x(i+1), L, x(i+m-1)] \tag{9}$$

where $i = 1, L, N - m + 1$.

(2) The distance between $X(x)$ and $X(j)$ is calculated and expressed by $d[X(i), X(j)]$,

$$d[X(i), X(j)] = \max_{k=0,L,m-1} \{|x(i+k) - x(j+k)|\} \tag{10}$$

(3) $Num\{d[X(i), X(j)] < r\}$ is the vector numbers of the distance between $X(x)$ and $X(j)$ which is less than r. $B_i^m(r)$ is the ratio of $Num\{d[X(i), X(j)] < r\}$ and $N - m$

$$B_i^m(r) = \frac{1}{N-m} Num\{d[X(i), X(j)] < r\} \tag{11}$$

where $i, j = 1, L, N - m + 1,\ i \neq j$.

$B^m(r)$ is the mean value of $B_i^m(r)$

$$B^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} B_i^m(r) \tag{12}$$

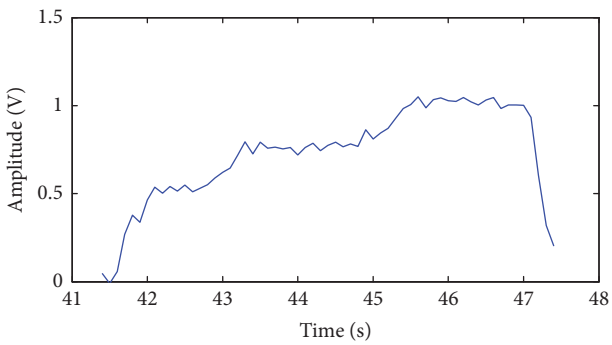

Figure 4: Chosen data in gentle braking process.

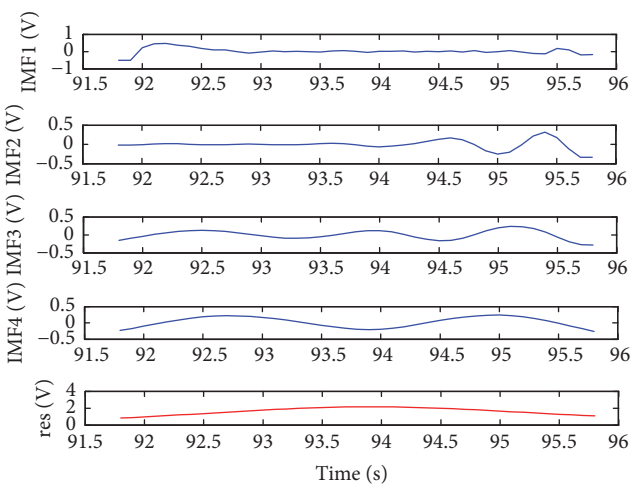

Figure 5: The component of IMF of moderate braking signal.

(4) $B^{m+1}(r)$ can be gotten by repeating the steps above

$$B^{m+1}(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} B_i^{m+1}(r) \tag{13}$$

(5) The sample entropy is obtained

$$SampEn(m,r) = \lim_{N\longrightarrow\infty}\left\{-\ln\frac{B^{m+1}(r)}{B^m(r)}\right\} \tag{14}$$

When N is finite, the sample entropy is approximately equal to the equation under

$$SampEn(m,r) = -\ln\frac{B^{m+1}(r)}{B^m(r)} \tag{15}$$

The features of moderate and gentle braking signals are extracted, by using sample entropy of the IMFs, which is shown in Figures 7 and 8

3.2. The Selection of IMF Component Feature. After the brake pedal signal is decomposed by EMD, many IMFs can be obtained. The amount of calculation is too large if the sample entropy is calculated for all IMF components, which make the feature extraction inefficient. Therefore, the IMFs should be filtered. The IMFs with more information are chosen to calculate their sample entropies as the signal's feature. The Shannon entropy is used to choose which IMFs' sample entropies can be used as the features of the brake pedal travel signal in this paper.

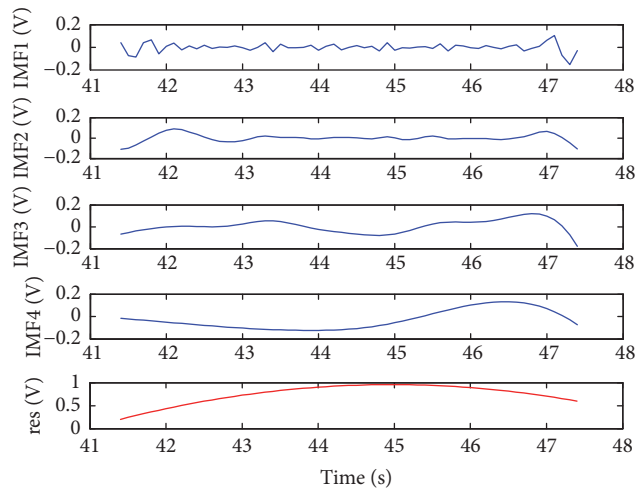

Figure 6: The component of IMF of gentle braking signal.

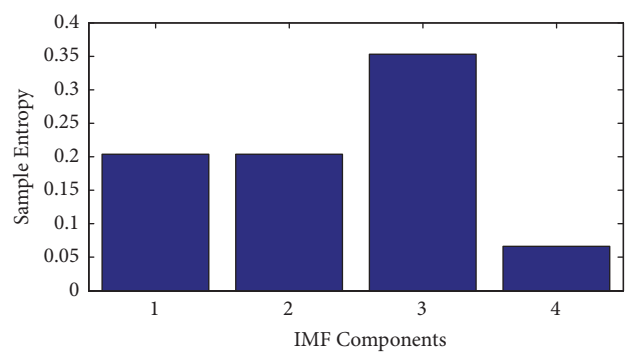

Figure 7: The sample entropy of the IMF component of moderate braking.

$\{c_i\}$ is the IMF of the signal decomposed by EMD, where $1 \le i \le n$. $H(c_i)$ is the Shannon entropy of each $\{c_i\}$. γ is threshold value, which is the mean value of the Shannon entropy of each IMF. If the Shannon entropy of an IMF is larger than γ, it indicates that the information of the IMF is useful to extract the signal features. Otherwise, the IMF should be abandoned.

$$H(c_i) = -\sum_{j=1}^{n} p_j \log p_j \tag{16}$$

where p_j is the probability of the value of the jth element of $\{c_i\}$

Figures 9 and 10 are the Shannon entropy of the IMFs of the pedal signal, and the horizontal line is the threshold value of the Shannon entropy. It can be seen that the third and fourth Shannon entropy of the IMFs of the moderate and gentle braking signal are larger than the threshold value. It can be used for feature extraction because it has more

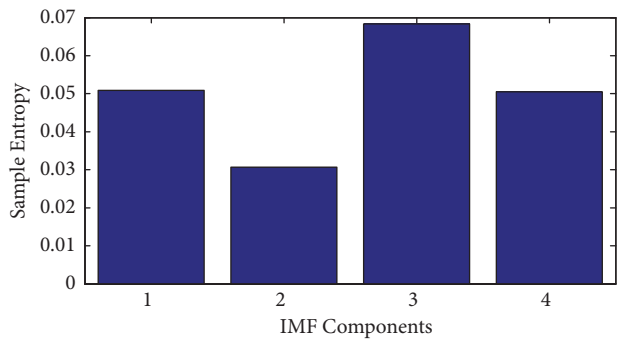

Figure 8: The sample entropy of the IMF component of gentle braking.

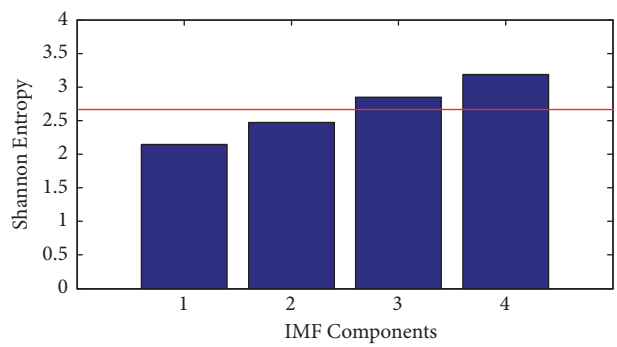

Figure 9: The Shannon entropy of the IMF component of the moderate brake pedal.

information and obvious features. In this paper, the third and fourth sample entropy of the IMFs of the brake pedal signal are used as the feature value of the feature vector. For example, the sample entropy of the last two IMFs is the feature values of the moderate and gentle braking signal feature vectors.

3.3. Braking Intention Identification. The feature vectors of the brake pedal travel signal data of different braking intentions can be clustered by fuzzy C-means clustering algorithm, which can give us clustering center of the brake pedal travel signal data of typical braking intentions. If the Euclidean distance between the real-time signal's feature vector and the clustering center of gentle braking is smaller than the threshold, then the brake pedal travel signal is identified as gentle braking. The moderate braking can be identified likewise. The threshold for identification is the max Euclidean distance between a typical braking pedal travel signal feature vector and its clustering center.

The core idea of the fuzzy C-means clustering algorithm is to find the clustering center of the sample, which makes the sum of squares of the weighted distances from the sample to the cluster center minimum. The objective function of this algorithm is shown in

$$J(U,Z) = \sum_{i=1}^{C}\sum_{j=1}^{n}\left(\mu_{ij}\right)^{m}\left(d_{ij}\right)^{2} \tag{17}$$

where μ_{ij} is the degree of membership which indicates the ith sample belongs to j^{th} braking intention. d_{ij} is the Euclidean

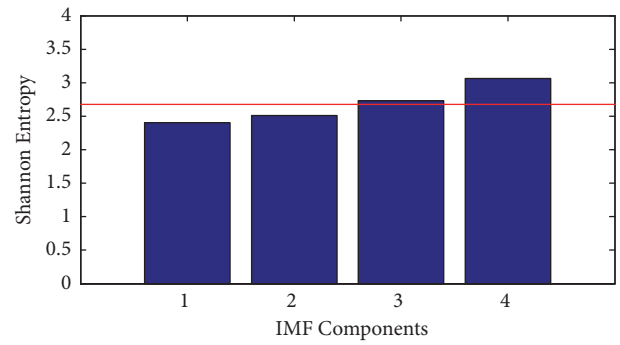

Figure 10: The Shannon entropy of the IMF component of the gentle brake pedal.

distance from a sample x_j to the clustering center of ith braking intention, which can be expressed as $d_{ij}(x_j, z_i) = \|x_j - z_i\|$. Z is the clustering center, which can be expressed as $Z = (z_1, z_2, \cdots z_c)$. m is the weighted index. C is the category numbers of braking intentions, which means sample set $\{x_1, x_2, \cdots, x_n\}$ can be classified into C kinds of braking intentions. U is the initial membership matrix. The iterative equations of the fuzzy C-means clustering algorithm are shown in (18) and (19). The iterative termination condition is shown in (20). n is the number of samples. ε is the terminal threshold of iteration. $Z^{(0)}$ is the initial clustering center. $Z^{(p)}$ is the clustering center of the pth iteration. p is the iteration numbers.

$$\mu_{ij}^{(p)} = \frac{1}{\sum_{k=1}^{C}\left(d_{ij}^{(p)}/d_{kj}^{(p)}\right)^{2/(m-1)}} \tag{18}$$

where $i = 1, 2, \cdots, C,\ \ j = 1, 2, \cdots, n$.

$$z_i^{(p+1)} = \frac{\sum_{j=1}^{n}\left(\mu_{ij}^{(p+1)}\right)^{m} x_j}{\sum_{j=1}^{n}\left(\mu_{ij}^{(p+1)}\right)^{m}} \tag{19}$$

where $i = 1, 2, \cdots, C$.

$$\left\|Z^{(p)} - Z^{(p+1)}\right\| < \varepsilon \tag{20}$$

4. Experimental Verification

4.1. Offline Verification. 100 groups of brake pedal signals of the moderate and gentle braking are selected as test samples. Test samples 1st-50th are for moderate braking and 51st-100th for gentle braking. The fuzzy C-means clustering algorithm for braking intention identification based on EMD and entropy theory is verified offline in MATLAB. The identification results are shown in Figure 11. It can be seen from Figure 11 that the samples of the brake pedal signals are classified into two types of braking intentions by recognition algorithm. In Figure 11, triangles indicate gentle braking and circles for moderate braking. The two stars in Figure 11 are clustering centers of moderate and gentle braking.

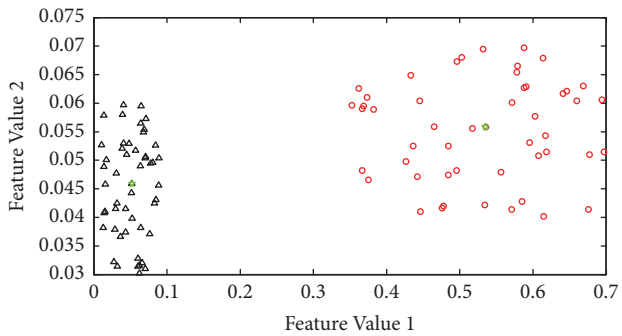

Figure 11: Offline identification result.

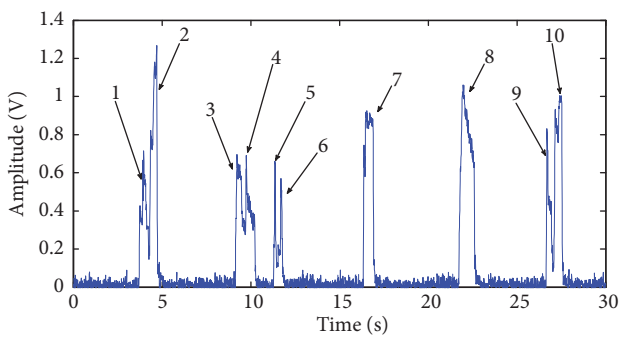

Figure 12: Real-time brake pedal signal.

4.2. Real-Time Verification. The vehicle used for real-time verification is a hybrid bus. The hardware for data collection, processing, and identification is dSPACE/MicroAutoBox1401/1504 compatible with software MATLAB. The brake pedal signal of the prototype vehicle is a switch signal, whose value is 0 or 1. It cannot be used directly to identify the braking intention. Therefore, a sensor is made to collect brake pedal signal. The brake pedal signal is input into the MicroAutoBox for online data processing and braking intention identification. The fuzzy c-means clustering identification algorithm based on EMD and entropy theory is downloaded into MicroAutoBox before online identification. The brake pedal signal and its corresponding braking intention are marked in Figure 12, in which numbers 1,2,5,6 are gentle braking and numbers 3,4,7,8,9,10 are moderate braking. The online identification result of the braking intention is shown in Figure 13, in which identification value 1.5 represents gentle braking and identification value 2 represents moderate braking. Also, in Figure 13, asterisks express identification result based on EMD and entropy theory, and circles express identification result based on logical threshold identification algorithm. It can be seen that all the driver's braking intentions can be identified accurately online by the algorithm proposed in this paper. There is one intention misidentified by logical threshold identification algorithm. Number 8 intention is moderate braking, but logical threshold identification algorithm misidentifies it as gentle braking. So, identification accuracy rate of logical threshold algorithm is 90%, while identification accuracy rate of the algorithm based on EMD and entropy theory is 100%. The online identification time that from the start of braking

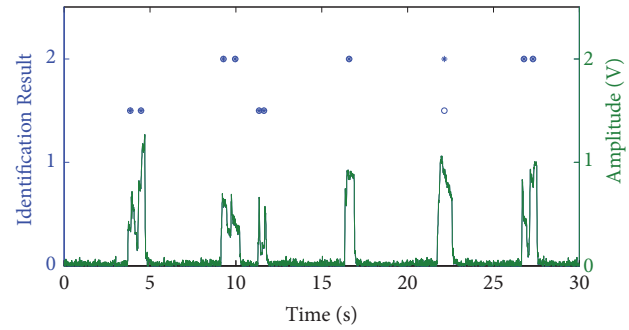

Figure 13: Online braking intention identification.

process to the first identification result obtained is 0.05s, which satisfies the demand shown in Figure 14.

5. Conclusion

(1) Fuzzy c-means clustering algorithm of braking intention identification based on EMD and entropy theory excavates the features of brake pedal signal to extract signal feature vectors, which can help identify moderate and gentle braking intention accurately. Offline experiments show that the algorithm proposed can classify two types of braking intentions accurately. And online experiments show that compared with the logical threshold identification method, the recognition accuracy is improved 10% by the proposed method.

(2) Fuzzy c-means clustering algorithm of braking intention identification based on EMD and entropy theory has good real-time performance. The real-time experiment proof that the braking intention can be identified accurately by the algorithm proposed within 0.05s, which is useful for the application of braking intention identification technology for electric vehicles regenerative braking.

6. Future Work

The features of braking pedal travel signal have been mined in time-frequency domain, by identification algorithm proposed in this paper, which improved identification accuracy. However, the clustering center for braking intention identification was calculated by clustering particular braking pedal travel signal data of chosen driver. So, it is difficult to ensure the accuracy of identification if the drivers are with different driving styles. Therefore, the future work should be to make the recognition algorithm have adaptability and the ability of self-learning, which means the accuracy of identification cannot be affected by driving styles. In the future, the deep learning algorithm should be used in the braking intention identification algorithm.

Data Availability

The experimental data used to support the findings of this study have been deposited in the Figshare repository. Logging in email and password are available from the corresponding author upon request.

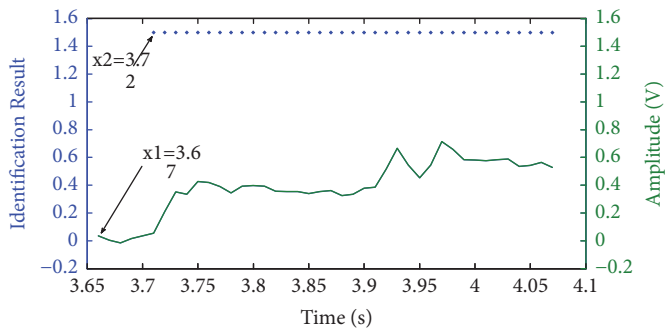

Figure 14: Respond time of online braking intention identification.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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