Electric vehicle regional management system based on the BSP model and multi-information fusion

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ABSTRACT
Aiming at the problem of most electric vehicles (EV) sounding false alarms due to touches, an EV alarm regionalization management control system based on multi-information fusion and the BSP model is designed in the present study. The proposed system uses multiple sensors to detect the state of the EV, and realizes multi-sensor information fusion by the Lagrange interpolation method. The ZigBee networking technology is used to carry out the regional management of EV alarms, establish a BSP model, realize the synchronous transmission of system status detection signals, and finally complete the alarm function. The experimental results show that the false alarm rate of traditional EV alarm systems is about 85.5%, that of alarm systems that perform state monitoring without information fusion is about 11.3%, and that of the proposed alarm system that performs multi-information fusion simultaneously is greatly reduced to about 0.5%.

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1. Introduction

Electric vehicles (EV) have become increasingly prominent, and while this universal means of transportation is convenient, it also generates noise pollution. The harsh alarm sound of EV often oscillates up and down, subjecting community residents to the sound for tens of seconds. About 85.5% of EV alarms are caused by someone keep touching EV and the continuous sound effect (the alarms are triggered by the sound of other alarms). For this reason, there are some EV alarm devices related to status monitoring that are available on the market. Generally, multiple sensors are used to monitor the status of EV to reduce the false alarm rates of traditional alarm devices. However, due to the problem of multi-sensor information fusion, the detection signal is not synchronized; therefore, when an alarm without multi-sensor information fusion is adopted, the false alarm rate of the EV will be about 11.3%, resulting in unnecessary noise pollution. To solve this problem, an EV regionalized management system based on multi-information fusion and the BSP (bulk synchronous parallel) model is designed in the present study.

The proposed system adopts three conditional detection modules for status detection. The GY-521MPU6050 triaxial digital gyroscope detects the tilt angle of the EV, the HC-SR501 body infrared module detects whether there is a person beside the vehicle, and the single-chip microcomputer detects whether someone is touching the vehicle. The collective management of the alarm of the EV canopy is realized via ZigBee networking technology, as is the regionalized control of the EV alarm.

The information cycle transmitted by the three conditional detection modules used in the system is out of sync, so multi-sensor information fusion is needed. Previous studies (Bin et al., 2019; Greenberg et al., 2020; Patra et al., 2020; Simjanoska et al., 2020) have adopted the traditional target-level fusion method for multi-sensor information fusion. The three conditional detection modules in the proposed system have different detection information cycles. Therefore, a robust and accurate time-domain method based on the target-level fusion method is proposed.

To improve the arbitrariness of real-time data detection, a discrete signal interpolation or fitting method is needed. Previous research (Sindareh-Esfahani & Pieper, 2019) has found that the piecewise fitting of impulse response using the least-squares method will cause the fitted signal to lose the data of base points to a certain extent; however, the proposed system requires the accurate data of each base point. Another study (Cheng & Kou, 2020) adopted the full phase spectrum to analyze signal interpolation and iteration. FFT was used to reduce the computational amount of the system in another previous study, but it was necessary to know the zero-sequence
signal (Feng et al., 2019). However, because the zero-sequence signal inserted in the frequency domain cannot be determined in this work, the Lagrange (Berriochoa et al., 2020) interpolation method is adopted to interpolate the received discrete signals and the obtained values are real and stable.

It is assumed that the regionalized management of EV in this system manages a total of $m$ EV, and $m$ ZigBee sub-stations are required to transmit data to the ZigBee terminus in parallel. The methods of parallel transmission can be divided into three types: the PRAM model, LogP model, and BSP model. The PRAM model used in some previous studies (Brodnik & Grgurovi, 2018; Mishra et al., 2019) has a small local storage capacity, which is not suitable for MIMD machines with a distributed storage structure, and requires all instructions to be carried out in the mode of latches, which is time-consuming. The LogP model is mainly applicable to the design of point-to-point messaging algorithm. For the Shared storage mode, the remote read operation will be deemed as two messages passing, and the influence of pipeline prefetching technology, cache-induced data inconsistency and Cache hit ratio on the calculation is not considered, which will bring data deviation to the system designed in this paper. In the present work, the BSP model (Allombert & Gava, 2020; Liu et al., 2020; Marquer & Gava, 2019) adopts obstacle synchronization mode to realize global synchronization by hardware, thus providing an effective way to execute tightly coupled synchronous parallel algorithm, and it’s adopted to divide $m$ supersteps into $m$ EV, which can effectively avoid the deadlock phenomenon. The fence can be synchronized according to the different lengths of the three signals in each superstep.

2. Initialization of vehicle state detection

There are two states of EV parking: vertical parking and oblique parking. Therefore, it is necessary to initialize the parking state of EV, i.e. to record the tilt angle of the parked EV. After setting the initial state, it can be used to detect three conditional signals within 10 s as the base. Each initialization setting corresponds to a new 10-s conditional detection period. A subsystem cycle diagram is illustrated in Figure 1.

The flow chart of vehicle status detection and system setup is presented in Figure 2.

Based on the initial tilt angle, the initial parking state of the EV is set and the initial parking angle is input. Within the unit of 1 s, the three condition detection modules send the real-time data of the tilt angle of the EV, whether there is a person beside the EV, and whether someone is touching the EV. To make the result arbitrary, a continuous discrete signal can be obtained to determine whether the detection result reaches the threshold within any 10-s period. If the threshold value is not reached, the data sent
per second is returned. If the threshold is reached, the system determines that someone stole the electric car at this time, and the ZigBee sub-station transmits the alarm information to the ZigBee terminus. The terminus queries the serial number of the stolen electric car, and the system alarmed and sends the alarm information to the user’s mobile phone.

3. Multi-sensor information fusion based on continuous discrete signal

The information fusion method can be roughly classified into the data-level and target-level fusion methods. For this system, it is more suitable for the target-level fusion method, that is, the target information of each sensor is sent separately for detection, and the measurement data of multiple sensors of the whole system are comprehensively judged. This method has strong robustness and accuracy.

Each sub-station of the system has three condition detection modules: the GY-521MPU6050 triaxial digital gyroscope sensor module, the HC-SR501 human body infrared detection module, and the single-chip microcomputer detection shrapnel. These modules respectively detect the information of the tilt angle of the EV, whether someone is beside the EV, and whether the EV is being continuously touched.

Via the analysis of the three condition detection modules, when it is determined that the tilt angle of the EV changed more than 10° in 5 s, someone is at the side of the car, and the microcomputer shrapnel vibrates continuously for more than 10 s, it is determined that someone is stealing the car and the alarm is triggered. Under other conditions, the alarm is not triggered. The condition detection module process is presented in Figure 3.

The angle information of the EV after parking, i.e. the tilt angle of the EV, is taken as the initial angle $\alpha_0$. The status information of the EV as detected by the three condition detection modules is transmitted once per second.

$$S = (\alpha, b, c),$$

where $\alpha$ represents the tilt angle of the EV and is used for determining whether there is a person beside the vehicle; if a person is detected, the value is considered as ‘1’; otherwise, it is ‘0’. Additionally, $c$ is used for determining whether someone is continuously touching the electric car; if someone is continuously touching the car, the value is ‘1’; otherwise, it is ‘0’.

![Figure 3. Flow chart of condition detection module.](image-url)
The EV status information is transmitted in $n$ seconds.

$$S_n = \begin{pmatrix} \alpha_0 x_0 & \alpha_1 x_1 & \ldots & \alpha_n x_n \\ b_0 x_0 & b_1 x_1 & \ldots & b_n x_n \\ c_0 x_0 & c_1 x_1 & \ldots & c_n x_n \end{pmatrix}$$

(2)

Suppose the cumulative touch function is $l(t)$, the accumulate the function of someone next to the electric car is $p(t)$, and the tilt angle function is $\alpha(t)$. At this time, the transfer information of the three condition detection modules is received, as shown in Figure 4.

### A. Signal interpolation

Set $y = f(x)$ for any value of $x$ satisfying the function $y_i = f(x_i), i = 0, 1, \ldots, n$.

According to the Lagrange quadratic interpolation method, the ‘vehicle tilt angle’ information is obtained by interpolation as follows.

$$S_n(\alpha) = \sum_{i=0}^{n} y_{ai} \prod_{j=0, j \neq i}^{n} \frac{x-x_{aj}}{x_{ai}-x_{aj}} \cdot \sum_{i=0}^{n} y_{bi} \prod_{j=0, j \neq i}^{n} \frac{x-x_{bj}}{x_{bi}-x_{bj}} \cdot \sum_{i=0}^{n} y_{ci} \prod_{j=0, j \neq i}^{n} \frac{x-x_{cj}}{x_{ci}-x_{cj}}$$

(3)

$$S_n(t) = \sum_{i=0}^{n} y_i \prod_{j=0, j \neq i}^{n} \frac{t-t_{ij}}{t_{ij}-t_{ij}}$$

(4)

According to the Lagrange linear interpolation method, the information of ‘whether someone is near the EV” and ‘whether someone is touching the EV” is interpolated as follows.

$$S_n(b) = \frac{(x-x_{b1})}{(x_{b0}-x_{b1})} y_0 + \frac{(x-x_{b0})}{(x_{b1}-x_{b0})} y_1$$

(5)

$$S_n(c) = \frac{(x-x_{c1})}{(x_{c0}-x_{c1})} y_0 + \frac{(x-x_{c0})}{(x_{c1}-x_{c0})} y_1$$

(6)

According to Equations (3–6), the interpolation results of the three conditional discrete signals can be obtained. The relative error is:

$$\Delta = \frac{S_n(x) - f(x)}{f(x)} \times 100\%.$$  

(7)

The discrete information shown in Figure 4 is transformed into continuous information via the Lagrange interpolation method, and the three condition detection information figures are obtained, as presented in Figure 5.

### B. Multi-sensor information fusion

According to the continuous signals obtained by interpolation, it is possible to cumulate the tilt angle of the EV in 10 s as measured by the GY-521MPU6050 three-axis digital gyroscope sensor module, whether someone is near the EV for 10 s as measured by the HC-SR501 human body infrared detection module, and whether someone is touching the EV for more than 5 seconds as measured by the single-chip microcomputer shrapnel.

The data of the three-axis digital gyroscope and the human body infrared detection module are accumulated simultaneously. When the tilt angle of the EV as measured by the three-axis digital gyroscope exceeds 10° and the human body infrared detection module detects the continuous presence of a person, the first threshold value is reached.
According to Figure 5, the equations for an EV experiencing human touch for 10 s are obtained as follows.

\[
\begin{align*}
 I(t) &= 1, \quad \Delta I(t) = 0 \quad t \in (t_0, t_0 + 10) \\
 p(t) &= 1, \quad \Delta p(t) = 0 \quad t \in (t_0, t_0 + 10)
\end{align*}
\] (8)

When these two conditions are met, the first threshold value is reached. At this time, it is judged whether the tilting angle of the EV exceeds 10° within 5 seconds in \( t \in (t_1, t_1 + 5) \):

\[
\Delta \alpha \geq 10^\circ, \quad t \in (t_1, t_1 + 5), \quad t_1 \in (t_0, t_0 + 5)
\] (9)

If this condition is met, the second threshold is reached. The system then determines that someone stole the EV, and sends the alarm information to the ZigBee terminal.

4. Parallel data transmission based on BSP model

The BSP model is an asynchronous MIMD-DM model that can transmit \( m \) supersteps, each of which requires three stages: a local computing stage, global communication stage, and fence synchronization stage. The calculation process is presented in Figure 6.

In Figure 6, \( a \), \( b \), and \( c \) respectively refer to the tilt angle information of the EV, whether there is someone beside the vehicle, and whether there is someone touching the vehicle. After a single-step calculation, (0/1) information is sent, where ‘0’ means that no one has stolen the EV, and ‘1’ means that someone has stolen the EV.

Because the system contains \( M \) EV, \( m \) overrun messages (0/1) will be sent in parallel every second. The parallel operation mode is presented in Figure 7.

If the substation receives \( h = 3 \) message, \( i = 10s \) is the global synchronization time interval, \( t' \) is the transmission establishment time, and \( b \) is the number of bytes in a communication transmission, then the communication overhead is:

\[
bh = 3b.
\] (10)

The data transmission time of the system is:

\[
t = bh + t' = 3b + t'.
\] (11)

To improve the performance of the BSP model as much as possible, the ratio of the number of local computations that can be completed by the processor per second to the amount of data that can be transmitted by the router per second can be expanded as much as possible.

The \( m \) superstep transfers the calculation result ‘0/1’, clears the data corresponding to ‘0’, and the data corresponding to ‘1’ can continue to be transmitted and responded to, which can greatly reduce data redundancy and improve the system operation efficiency.

5. Experimental result

The traditional alarm system, an alarm system with state monitoring but without information fusion, and the proposed alarm system with status detection and multi-sensor information fusion were tested, and data collection was carried out. The feasibility and necessity of the system designed in this paper were verified via data comparison.

A. erimental hardware design

The main body of the system is divided into three parts: T1, T2, and T3. The T1 area is the subsystem area (sub-node), the T2 area is the system information transmission content, and the T3 area is the system master station. The T1 area detects the surrounding environment information of the EV, and then transmits the serial number, verification information, alarm flag bit, working status bit,
and vehicle safety bit information of the EV through the T2 area. The T3 area transmits commands to the T1 area via network communication, and sends the alarm information to the user’s mobile phone through the gateway module. The overall structure is illustrated in Figure 8.

The subsystem consists of four components: G1 represents the remote information transmission module, G2 represents the condition detection module, G3 represents the MCU information processing module, and G4 represents the EV alarm system. The detailed structural diagram of the substation and the main station is presented in Figure 9.

First, the system uses the GY-521MPU6050 three-axis digital gyroscope sensor module, the HC-SR501 human body infrared detection module, and the single-chip microcomputer to respectively detect the tilt angle information of the EV, whether there is a person beside the EV, and whether there is a person continuously touching the electric vehicle. Specifically, it detects whether the tilt angle of the EV cumulative angular deflection more than 10° in 5 s, whether there is a person standing beside the vehicle for 10 s, and whether there is a person continuously touching the vehicle for 10 s. When these three conditions are met, the system judges that someone is stealing the EV at this time, and transmits the information to the ZigBee master station via short-range information transmission from the ZigBee substation.

The G3 component then begins to work. The ZigBee master station will check the received information through the information comparison device and...
information storage module, and then feed back the original information to the ZigBee master station by retrieving the vehicle serial number, vehicle status bit, and alarm trigger bit of the EV in the MCU master control center.

At the same time, the information backup is saved and sent to the user’s mobile phone remotely. At this time, the G4 component of the ZigBee substation triggers an alarm.

The hardware of the system is depicted in Figure 10. The single-chip microcomputer shrapnel is located on the ZigBee substation board. However, this figure only depicts a master station and a substation, which can be further expanded to a master station corresponding to $m$ sub stations, i.e. $M$ EV.

### B. Data collection and data simulation

The MIS touch data of 100 EV with traditional alarm systems, 100 EV without multi-sensor information fusion systems, and 100 EV with the proposed multi-sensor information fusion system were collected. According to the existing data, 500 groups of random data were generated by Excel, and the generated random data were imported into Matlab to obtain the false alarm rates of the three kinds of alarms, as presented in Figure 11.

It is evident from the results that, after eliminating gross errors, the false alarm rate of the traditional alarm was found to be about 85.5%. When the Lagrange interpolation method was used for the real-time monitoring of
the three states of the EV but the BSP model was not used for condition information fence synchronization, the false alarm rate was found to be about 11.3%. Finally, when the BSP model was used for condition information fence synchronization, the false alarm rate was found to be only about 0.5%.

6. Conclusion

A regional management system of EV based on the BSP model and multi-information fusion was designed in this work. First, three condition detection modules are used to detect the state of EV in real time, the BSP model is then used to solve the problem of asynchronous information transmission, and the actual data is finally measured. The issues of false alarms and system regional management are effectively solved, and the method is characterized high practicability and strong robustness.

Disclosure statement
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