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Research Article

Wireless Communication System and Its Application in Big Data Remote Monitoring and Decision-Making

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The development of computer technology has promoted the widespread application of unmanned technology. Remote monitoring of wireless devices is an application of unmanned technology. To improve the remote monitoring of wireless devices, this study establishes a remote monitoring and decision-making framework based on wireless communication systems. With the wireless communication system, signals that characterize the operating status of devices can be obtained in real-time. Based on the collected signals, the remote monitoring system can identify the current health status of wireless devices, thereby providing auxiliary decision-making for device operation. In the case study, the main engine of an unmanned surface vehicle is used as the study object. The results show that most of the relative errors corresponding to the state identification results of the established remote monitoring framework are within 5%. Moreover, the results present that the linear correlation coefficients between the predicted and real results are greater than 0.95. Therefore, the established remote monitoring framework based on the wireless communication system has good reliability in the state identification of wireless devices.

1. Introduction

Computer technology plays an increasingly important role in human production and life, and it promotes the application of unmanned technology. For instance, the appearance of automatic driving of ships can not only liberate the labor force but also improve the level of navigation safety; the unmanned technology of cars makes the car design does not need to consider the impact of the car on the human body, so it can adapt to more complex working conditions and then better play the car performance [1]; the use of unmanned aerial vehicles (UAVs) in modern warfare has greatly increased combat capabilities, and its unmanned nature can reduce casualties [2]. However, the above technologies all rely on stable and fast wireless signal transmission. Based on the wireless signal transmission, a large amount of real-time data generated by the unmanned terminal can be transmitted to the base station, thereby realizing the communication between the unmanned terminal and the base station [3]. Therefore, to promote the development of unmanned technology, it is necessary to develop wireless communication technology.

The wireless communication system mainly includes three parts: signal transmitting device, transmission medium, and signal receiving device [4]. The function of the signal transmitting device is to collect signals that can reflect the status of the unmanned terminal and then process the collected signals for transmission; the role of the transmission medium is to provide a medium for signal transmission; the function of the signal receiving device is to receive wireless signals and perform inverse signal processing. For wireless devices such as UAVs, to achieve remote real-time control, it is necessary to obtain signals representing the status of the wireless device in real-time at the base station, thereby judging the operating status of the wireless device and then deciding the next operation strategy [5]. Therefore, a wireless communication system between the base station and the wireless device is required. With the wireless signal communication system, the base station can receive a large number of wireless signals from the wireless device in real-time. These signals can be temperature signals, pressure signals, speed signals, etc., and they can reflect the real-time operating status of wireless devices [6].

Although the signals transmitted by the wireless communication system can reflect the operating status of wireless devices, the identification of some fault status requires a comprehensive analysis of multiple operating signals, and even these multiple signals do not exceed their respective normal ranges [7]. Hence, it is necessary to establish a mapping relationship between multiple signals and device status. Currently, many researchers tried to establish numerical models of devices [8, 9] and used the operating signals as the input of numerical models, thereby realizing the state identification of devices. However, it is difficult to establish an accurate numerical model for complex devices, such as UAVs and marine engines, that exhibit strong nonlinear and unsteady characteristics [10]. Besides, researchers also attempted to use expert systems to establish the mapping relationship between multiple operating signals and device status [11]. However, the expert system needs a lot of expert knowledge to construct the rule base, so it is very dependent on the expert experience, and the difference in expert levels may affect the reliability of the expert system [12]. Moreover, expert systems also have defects such as combinatorial explosion and lag in rule update. Hence, both model-based methods and knowledge-based methods have limitations in state identification, while data-driven methods are free of building numerical models and do not rely on expert knowledge [13], they make up for the shortcomings of model-based methods and knowledge-based methods in the state identification of complex systems. Meanwhile, the development of wireless communication technology and big data technology makes devices generate a large amount of data representing status information during the operation process. Therefore, in the background of big data, the data-driven method has a good application prospect in state identification.

Deep learning is a data-driven approach, and meanwhile, it is also a branch of big data technology [14]. Compared with traditional data-driven methods, which need to manually extract the feature information in the signal by means such as Fourier transform, deep learning can adaptively extract the feature information in the signal without relying on manual experience [15]. Besides, based on the extracted feature information, deep learning can directly output state identification results. Therefore, compared with traditional data-driven methods, deep learning can achieve end-to-end state identification with the support of big data [16]. With the signals representing the status of devices obtained by the wireless communication system, deep learning methods can directly identify the status information of devices.

Based on the above analysis, to promote the further development of unmanned technology, this study proposes a remote monitoring and decision-making framework for wireless devices. The framework is mainly composed of two parts: a wireless communication system and a deep learning-based state identification system. With the output of the established framework, it can not only realize the remote status monitoring of wireless devices but also provide auxiliary decisions for the device's operation. In the process of quantifying the performance of the established state identification system, two statistical parameters, relative error and correlation coefficient, are used to evaluate the identification accuracy of the state identification system.

This study is organized as follows: Section 1 introduces the research background of the study, and it also describes the role of wireless communication systems and the application of big data technology in condition monitoring and decision-making. Section 2 describes the progress of related research works. In Section 3, the established remote monitoring and the decision-making framework for wireless devices is presented. Section 4 presents the data preparation for the case study. In Section 5, the feasibility and reliability of the established remote monitoring and the decision-making framework for wireless devices are analyzed. Section 6 is the conclusion of this study.

2. Related Work

As wireless communication systems play an increasingly important role in the development of unmanned technology, many scholars have invested a lot of research into wireless communication systems.

Ojaroudi Parchin et al. [17] described the current and future development of wireless communication systems and explored the feasibility of using reconfigurable antennas with multifunctional and small-sized devices in wireless communication systems. The research results showed that the wireless communication system is very suitable for 4G and 5G terminals. Then, to improve the reliability of wireless communication systems in practical applications, Bakare and Enoch [18] reviewed the commonly used simulation methods in recent years and analyzed the layout strategies of wireless communication systems in complex systems through simulation cases. Thereafter, to improve the efficiency, capacity, and reliability of wireless communication systems in signal transmission, Chowdhury et al. [19] prospected the application of the 6G wireless communication system. The content of the article showed that the development of 6G will provide strong assistance for the further development of unmanned technology.

With the further development of the wireless communication system, the signal representing the status of wireless devices can be obtained more conveniently at the base station. Based on the obtained status signals, researchers have made some progress in the remote monitoring of devices.

Rekha et al. [20] built a real-time embedded system for traffic monitoring. The system takes advantage of the wireless communication system without wiring and can monitor the status of wireless devices. Besides, to reduce energy consumption, Alulema et al. [21] built a wireless sensor network to realize remote monitoring of household electricity consumption. The results indicated that the built wireless network not only has high precision but also has a simpler structure than traditional wired devices. Thereafter, in the background of COVID-19, based on the Internet of Things technology, Paganelli et al. [22] used wireless

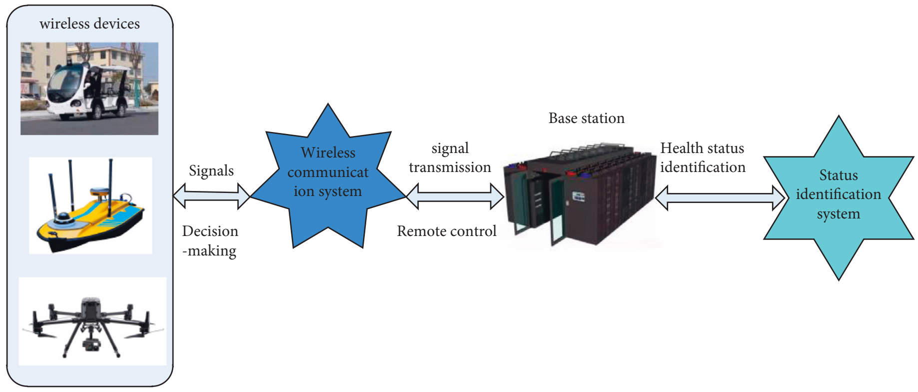

FIGURE 1: Remote monitoring and decision-making framework for wireless devices.

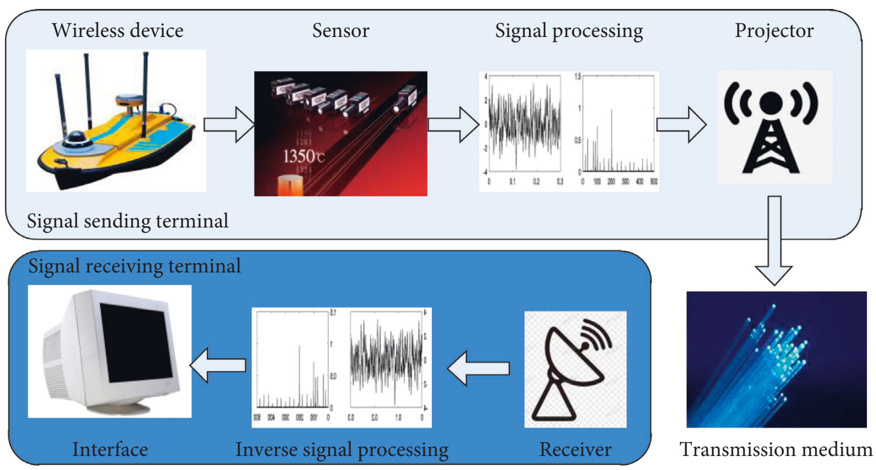

FIGURE 2: Diagram for the wireless communication system.

wearable sensors to collect the physical information of COVID-19 patients, thereby providing data support for remote monitoring of the patient's physical status.

According to the aforementioned description, researchers have attempted to build more efficient wireless communication systems. Besides, they also tried to realize the status monitoring of wireless devices based on signals. However, most of the existing research is to improve the wireless communication system or the remote monitoring system of the wireless equipment alone, and few explore how to improve the overall framework of the remote monitoring system based on the wireless communication system.

3. Methodology

In the background of big data, to realize the remote control of wireless devices, this study establishes remote monitoring and decision-making framework for wireless devices. The schematic diagram of the framework is shown in Figure 1. As can be seen from Figure 1, the established framework is mainly divided into two parts: the wireless communication system and the state identification system. In the following, the details and roles of the two subsystems are introduced, respectively.

3.1. Wireless Communication System. To remotely monitor the condition of wireless devices, signals characterizing the condition of wireless devices are necessary. So, a wireless communication system between the wireless device and the base station is required. In this study, the established wireless communication system is shown in Figure 2. As can be seen from Figure 2, the wireless communication system consists of three parts: signal acquisition and transmission device, transmission medium, and signal receiving device.

For the signal acquisition and the transmission device, various sensors, such as temperature sensors and pressure sensors, collect signals representing the status of the wireless device; then, signal processing methods are used to process the collected signals to facilitate signal transmission; thereafter, the signal transmitting device transmits the processed signal into the signal transmission medium.

The signal transmission medium is the medium of signal transmission between the wireless device and the base station, which can be water or air. Since the signal transmission characteristics of different types of transmission mediums are very different, to optimize the transmission efficiency of signals, it is necessary to adopt a signal processing method matching the transmission medium in the signal acquisition and transmission device.

For the signal receiving device, firstly, signals from the transmission medium are received through the device; then, the signal is inversely processed with the signal processing method corresponding to the signal acquisition and transmission device; finally, signals that can characterize the operating status of the device is obtained at the output end of the wireless communication system.

Based on the established wireless communication system, a bridge of signal transmission is built between wireless devices and base stations, thereby providing data support for the remote control of wireless devices.

3.2. State Identification System. With wireless communication systems, signals that characterize the operational status of wireless devices can be obtained. For simple systems, it is possible to directly derive the health status of devices by analyzing the relationship between these signals and the normal operating range. However, when a complex device fails, many of the acquired signals may still be within the normal range. At this time, the health status of devices cannot be directly judged through the value range of signals. Therefore, to analyze the health status of a complex wireless device, it is necessary to establish a mapping relationship between multiple signals and device status. With the established mapping relationship, the influence of multiple signals is comprehensively analyzed to monitor the operating status of wireless devices.

Considering the large amount of data generated in the operation of wireless devices, and deep learning methods are good at mining latent feature information from big data, this study established a state identification system based on deep learning. The established deep learning-based state identification system is shown in Figure 3. Based on the big data support provided by the wireless communication system, the deep learning method can establish the mapping relationship between multiple signals and the status of the wireless device. Then, the deep learning-based state identification system can monitor the status information of wireless devices in real-time and provide auxiliary decision-making for device operation.

As can be seen from Figure 3, the deep learning-based state identification system is mainly divided into two parts: feature extractor and state identification. In the following, the roles of these two parts are described separately.

3.2.1. Feature Extractor. The feature extractor is used to adaptively extract feature information from signals. Since the signals collected by the wireless communication system are usually in the form of sequences, to extract as much feature information of the signals as possible, the long-short-term memory (LSTM) network is applied in this study.

LSTM is a variant of recurrent neural network (RNN) [23]. Although RNN can extract the feature information in the sequence, in the process of using RNN to extract the feature information of the long sequence, the problem of gradient disappearance or gradient explosion will occur, which seriously affects the training efficiency of the RNN and reduces the quality of the extracted feature information. LSTM introduces control gates, which can alleviate the problem of gradient anomalies in long-sequence applications. The structure diagram of LSTM is shown in Figure 4.

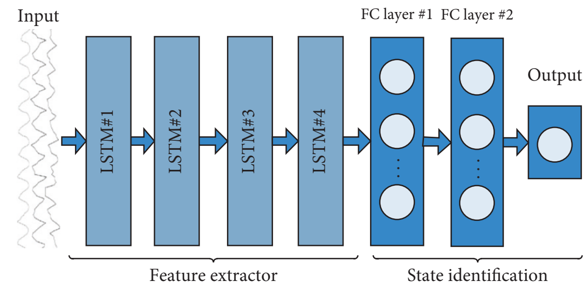

Figure 3: Structure for the deep learning-based state identification system.

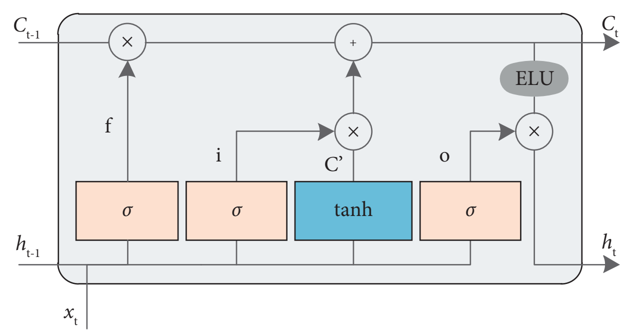

Figure 4: Structure diagram of LSTM.

As can be seen from Figure 4, LSTM is mainly composed of three control gates: the forgetting gate, the input gate, and the output gate. The mathematical expressions of the three control gates are equations (1)–(3), respectively.

$$f_t = \sigma\left(W_f \cdot x_t + W_f \cdot h_{t-1} + b_f\right), \tag{1}$$

$$i_t = \sigma\left(W_i \cdot x_t + W_i \cdot h_{t-1} + b_i\right), \tag{2}$$

$$o_t = \sigma\left(W_o \cdot x_t + W_o \cdot h_{t-1} + b_o\right), \tag{3}$$

where σ is the sigmoid activation function, W_f, W_i, and W_o are the weights corresponding to the forgetting gate, the input gate, and the output gate, respectively, b_f, b_i, and b_o are the biases corresponding to the forgetting gate, the input gate, and the output gate, respectively, x_t is the input at time t, h_{t-1} is the hidden layer state at time t-1.

Among the three control gates, the forgetting gate can selectively forget part of the previous memory information, thereby reducing the redundancy of the extracted feature information; the input gate is used to perform the nonlinear transformation on the current input to enrich feature information; the output gate is used to determine the feature information that needs to be output.

Based on the outputs of the three control gates, the state and output of the LSTM cell at time t can be obtained, and the expressions of the cell state and cell output of LSTM are equations (4) and (5), respectively.

$$C_t = f_t \circ C_{t-1} + i_t \circ C^{'}_{t-1}), \quad (4)$$

$$h_t = o_t \circ \mathrm{ELU}(C_t), \quad (5)$$

where $C_{t\text{-}1}$ represents the cell state of LSTM at time t-1, $\circ$ denotes an element-wise multiplication operation, and the expression of $C'_{t\text{-}1}$ is

$$C^{'}_{t-1} = \tan(W_C \cdot x_t + W_C \cdot h_{t-1} + b_C). \quad (6)$$

Note that the exponential linear unit (ELU) is an improved activation function that makes the distribution of network layers close to a zero-centered distribution [24], thereby alleviating the problem of gradient anomalies in the network. The mathematical expression of ELU is

$$y = \begin{cases} \alpha(e^x - 1)(x \le 0), \\ x(x > 0), \end{cases} \quad (7)$$

where α is a constant, and α is set as 1 in this study.

The above are the specific details of the LSTM network. Besides, Figure 4 points out that in the established state identification system, four LSTM layers with the same structure are applied, which is to extract the feature information contained in the multidimensional sequence signal as adequately as possible by using the deep learning method.

3.2.2. State Identification. With the feature information extracted by the feature extractor, a state identification unit is needed to establish a mapping between the feature information and the status of the wireless device.

In this study, as shown in Figure 4, fully connected (FC) layers are used to establish the mapping relationship between feature information and device status, and its mathematical expression is

$$\mathrm{full}_k = f\left(\sum_{n=1}^{N} x_n w_{n,k} + b_k\right), \quad (8)$$

where $full_k$ is the kth neuron output in the output layer, x_n is the input of the FC layer, w and b are the weight and bias, respectively, and $f(\cdot)$ is the activation function. Herein, ELU is used as the activation function of FC layers.

Based on the output of the state identification unit, the health status of the wireless device can be identified.

3.3. Workflow of the Remote Monitoring and the Decision-Making Framework. According to the aforementioned description, the specific workflow of the remote monitoring and decision-making for wireless devices is shown in Figure 5, and its specific details are as follows:

(i) Data collection. The signals that characterize the operating status of the wireless device are collected through the wireless communication system.

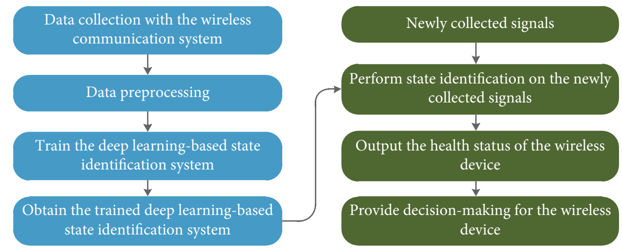

Figure 5: Workflow for the remote monitoring and decision-making framework.

(ii) Data preprocessing. Since the signals collected through the wireless communication system will inevitably have data anomalies, such as missing data, it is necessary to perform data preprocessing on the collected signals, such as supplementing missing values, removing outliers, and regularization.

(iii) State identification. Taking the preprocessed data as input, the state identification system can automatically output the wireless device state information at the current moment, thereby realizing the remote monitoring of the wireless device. Meanwhile, the output of the state identification system can provide auxiliary decision-making for device operation. Note that before applying the state identification system, the state identification system needs to be trained to achieve a certain identification accuracy. In this study, the back-propagation algorithm is adopted to train the deep learning-based state identification system. The training process mainly includes: (1) the calculation of the loss function. The mean squared error (MSE) is used for the loss function, and its expression is

$$\mathrm{MSE} = \frac{1}{N}\sum\left(y_{\mathrm{pre}} - y_{\mathrm{real}}\right)^2, \quad (9)$$

where y_{pre} and y_{real} are the predicted and real device status, respectively, and N is the number of samples; (2) calculate the gradient of the loss function on the trainable parameters and update the trainable parameters, and the expression for updating parameters is

$$\theta = \theta - r \cdot g(\theta), \quad (10)$$

where θ and r are the trainable parameter and the learning rate, respectively; (3) repeat the above steps (1) and (2) until the preset training accuracy is met.

4. Case Study

To explore the effectiveness of the established remote monitoring and the decision-making framework for wireless devices, this study takes an unmanned surface vehicle (USV) as an example to analyze the performance of the established framework in the remote monitoring of the USV's main engine.

To monitor the operating status of the main engine in real-time at the base station, multiple signals representing the operating status of the main engine are transmitted to the base station through a wireless communication system. The monitored signals include the pressure signal, temperature signal, and speed signal.

Before using the established state identification system to analyze the collected signal sequence, the deep learning-based state identification system needs to be trained first. In this study, the state identification system is trained using a large amount of data obtained from the wireless communication system in the base station.

Since the collected signal sequences have different dimensions and amplitudes, and as indicated in Ref. [25], the standard normal distribution is conducive to improve the network training efficiency, the Z-score standardization method [26] is used to process the collected signals to ensure the training efficiency of the deep learning method and the effect of state identification. The mathematical expression for normalizing the signals is

$$Nor = \frac{X - \mu}{\sigma}, \tag{11}$$

where $X = \{x_1, x_2, \ldots, x_n\}$ represents the signal sequence, μ is the mean of the vector X, and σ is the standard deviation of the vector X. With Z-score standardization, the processed signal follows a standard normal distribution. Note that because different types of signals have different dimensions, each type of signal is processed separately by (11).

To train the established state identification system and explore the identification accuracy of the trained state identification system, the processed signals are divided into 15 groups according to the navigational speed of USV. Among them, each group of signals contains 100 samples. The variable composition of each sample is (s, X_1, X_2, X_3), where s represents the health status of the main engine, and X_1, X_2, and X_3 represent the temperature sequence, pressure sequence, and speed sequence, respectively. In this study, the value range of s is [0, 100], and the larger the s is, the healthier the engine is. Thereafter, the 15 sets of signals are divided into the training set, validation set, and testing set. The specific division details are shown in Table 1. Among them, the training set and the verification set are used to train the deep learning-based state identification system; the testing set is used to verify the identification accuracy of the trained state identification system. Note that the navigational speed corresponding to the testing set is outside the range of the speed corresponding to the training set and the validation set, this is to ensure the reliability of evaluating the performance of the state identification system on the testing set. Based on the divided datasets, the identification accuracy of the established state identification system can be evaluated.

Table 1: Dividing details of the dataset.

Data set	Navigational speed (Kn)
Training set	[3.5, 4, 4.5, 5.5, 6, 6.5, 7.5, 8, 8.5, 9.5]
Validation set	[5, 7, 9]
Testing set	[3, 10]

5. Results and Discussion

5.1. Evaluation of the Performance of the Established Framework. After the deep learning-based state identification system is trained, its prediction performance on the testing set is evaluated in this subsection. Notably, the hyperparameters in the deep learning-based state identification system are set as [32, 64, 32], where the first "100" represents the number of units in four LSTM layers, and "64" and the second "32" are the number of neurons in FC layers.

As can be seen from Table 1, the corresponding navigational speed of the testing set is 3 or 10. Under the two navigational speeds, the comparison between the health state of the main engine predicted by the state identification system and the real health status is shown in Figure 6. It can be seen from Figures 6(a) and 6(b) that although the difference between the predicted and real health status under the speed = 3 Kn is slightly bigger than that under the speed = 10 Kn, the predicted and real health status at both navigational speeds are all closed.

To present the difference between the predicted and real health status more clearly, the relative error between the predicted and real health status is calculated. The expression of the relative error is

$$RE = \frac{\mathrm{abs}\left(y_{\mathrm{pre}} - y_{\mathrm{real}}\right)}{y_{\mathrm{real}}}, \tag{12}$$

where y_{pre} and y_{real} represent the predicted and real health status, respectively, and abs(·) represents the operation to calculate the absolute value. Figure 7 presents the relative error distributions corresponding to the two navigational speeds. It can be seen from Figure 7 that most of the relative errors under the two navigational speeds are less than 5%, and even at speed = 10 Kn, the relative errors are basically within 3%. Moreover, the average relative errors between the predicted and real health status under the two navigational speeds are shown in Figure 8. As can be seen from Figure 8, the average relative errors under the two navigational speeds are 1.1256% and 2.0315%, respectively.

As indicated in Ref. [27], 5% is an acceptable relative error for state identification accuracy. So, from the perspective of the relative error, the results reveal that the predicted and real health status are in good agreement, which confirms the reliability of the established state identification system in health status identification.

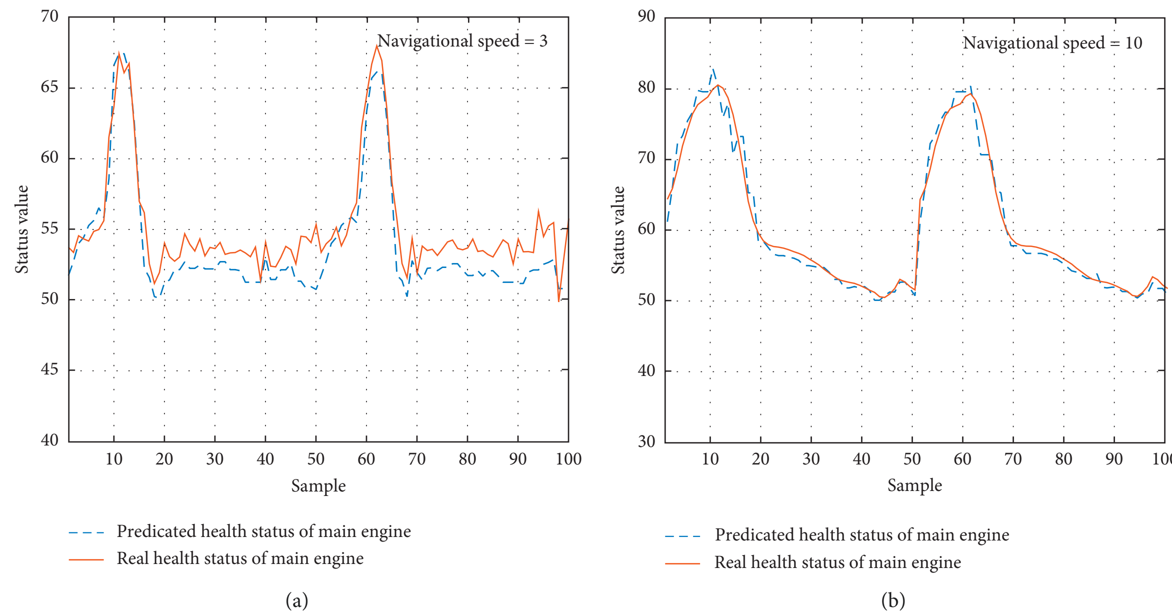

Figure 6: Comparison of the predicted and real health status of the main engine under two navigational speeds: (a) navigational speed = 3; (b) navigational speed = 10.

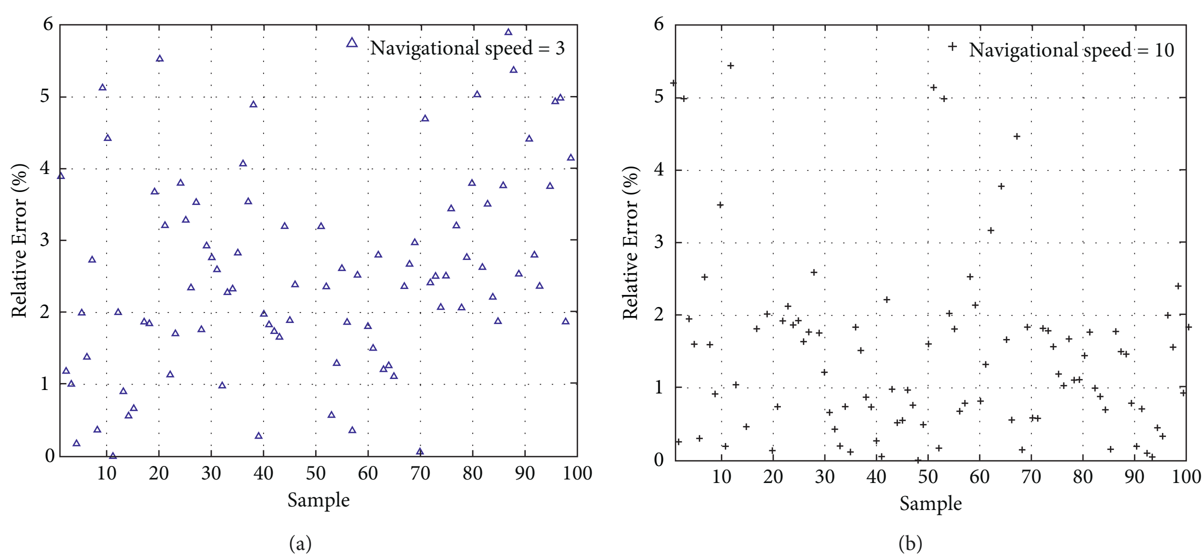

Figure 7: Relative errors between the predicted and real health status of the main engine under two navigational speeds: (a) navigational speed = 3; (b) navigational speed = 10.

5.2. Statistical Analysis. To further verify the performance of the established state identification system in health status identification, the results are statistically analyzed in this subsection.

Firstly, MSE between the predicted and real health status under the two navigational speeds is calculated, and the formula for calculating MSE is equation (9). Figure 9 shows that MSE under the two navigational speeds is 2.8956 and 1.5256, respectively, which shows that the MSE values are small at both navigational speeds. Since the health status of the main engine is in the range of [0, 100] in this study, the MSE results indicate that the predicted and real health status

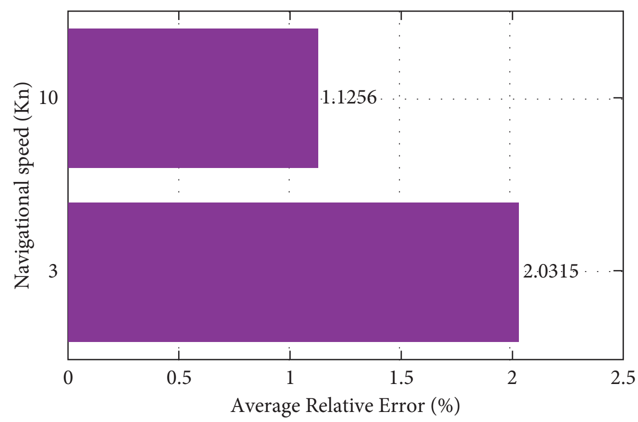

Figure 8: Average relative errors between the predicted and real health status of the main engine under two navigational speeds.

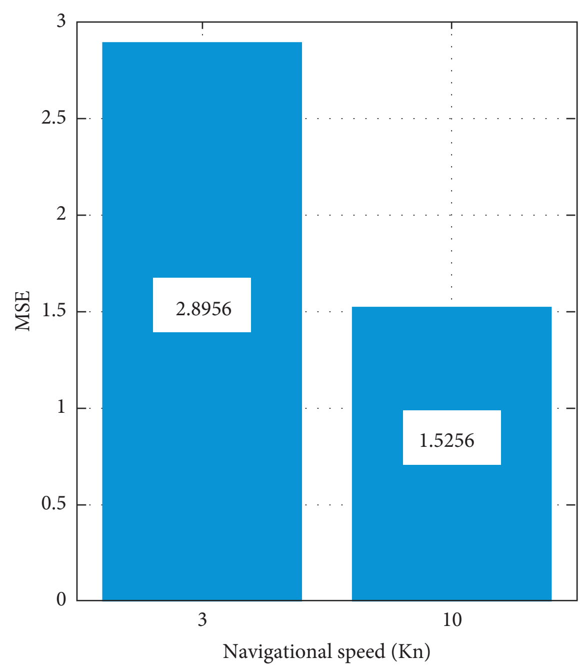

Figure 9: MSE between the predicted and real health status of the main engine under two navigational speeds.

are very close to each other under the two navigational speeds.

Secondly, the linear correlation between the predicted and real health status is also analyzed. Figure 10 presents the correlation results between the predicted and real health status under the two navigational speeds. As can be seen from Figure 10, the data points consisting of the predicted and real health status are close to the line $y = x$ under both navigational speeds. Moreover, Figure 10 shows that the linear correlation coefficients under the two navigational speeds are 0.9510 and 0.9881, respectively. Hence, the results reveal a strong linear correlation between the predicted and real health status.

Therefore, from the perspective of statistical analysis of the results, it is further shown that based on the signals collected by the wireless communication system, the established state identification system is reliable in identifying the health status of wireless devices.

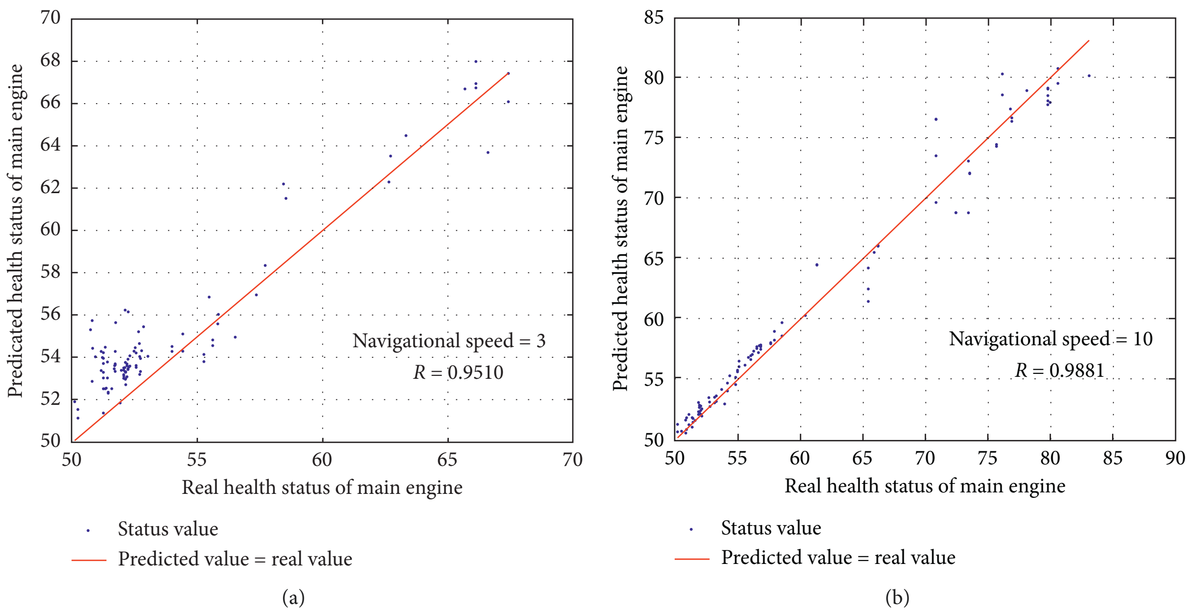

Figure 10: Linear correlation between the predicted and real health status of the main engine under two navigational speeds: (a) navigational speed = 3; (b) navigational speed = 10.

6. Conclusion

In this study, based on the signals that characterize the status of devices collected by the wireless communication system, a remote monitoring and a decision-making framework for wireless devices is established. The established framework can monitor the status of wireless devices in real-time by analyzing signals and can provide auxiliary decision-making for device operation. With a case study, the performance of the established framework in wireless device state identification is analyzed. The results are summarized below.

Comparing the predicted and real health status under the two navigational speeds on the testing set, the results reveal that the relative error at both navigational speeds is mostly within 5%, which indicates that the predicted and real health status have strong consistency.

According to the statistical analysis results, the correlation coefficients between the predicted and real health status under the two navigational speeds are 0.9510 and 0.9881, respectively, which reveals a strong linear correlation between the predicted and real results.

Based on the relative error and linear correlation results, it is revealed that the established framework has high prediction accuracy for the health status of wireless devices. Moreover, since the navigational speed on the testing set is outside the range of the training set and the validation set, the established framework also has extrapolation abilities in the state identification.

Although the established remote monitoring framework can achieve good accuracy in the background of big data provided by wireless communication systems, it needs to accumulate numerous historical data to train the state recognition system. In the future, we will explore more intelligent remote monitoring and decision-making frameworks.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that they have no conflicts of interest.

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