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The Intelligent Fault Diagnosis System Design with Augmented Reality for Electric Motors

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Abstract: With the rapid development of industrial automation technology, electric motors have developed into an important technology in life. However, motor faults have many possible causes, and it is not easy to detect in advance. Therefore, the fault diagnosis technology of motors is an important issue in recent years. Augmented reality (AR) technology has also been rapidly developing in recent years towards various industrial and educational applications. The AR technology is also suitable for the design and fault diagnosis of electric motors. This research is focused on the development and integration of intelligent diagnosis system and AR application for electric motors. The intelligent diagnosis system also applies cloud data management and machine learning methods to predict the health status and the possible abnormalities of electric motors. The time-recurrent Long Short-Term Memory (LSTM) neural network algorithm is applied to establish a motor health diagnostic model. The experimental results show that the motor diagnosis method can predict the health status of motor effectively. The AR technology can also displays the alarm signals of the digital electric motor model on the mobile devices immediately to provide a convenient and efficient management mechanism. The proposed system can also provide more industrial application services in the future.
Keywords: Diagnosis system, Electric motors, Augmented reality, Machine learning, LSTM.

1. Introduction

Many devices in our life are related to the electric motors, such as the engine of a car, or electric fan and so on. It is also widely used in the machinery industry, electrical machinery industry, medical industry, etc., and also used in the field of automation control and electromechanical integration. The motor can convert electrical energy into mechanical energy to drive for vibration, rotation, and linear motion. There are many different types of motors, which are mainly composed of stators and rotors. The stator is stationary in the space, while the rotor can rotate around the shaft and is supported by bearings. There is a certain air gap between the stator and the rotor to ensure the rotor can rotate freely. The stator and rotor are wound with coils, and current is applied to generate a magnetic field, which becomes an electromagnet.

When the motor is running, it will be accompanied by vibration. When the motor runs with abnormal vibration, it indicates that the faults may occur. For the motor, when it faults, it can be diagnosed through various vibration analysis methods. There are some researches discussed about motor fault diagnosis methods [1,2], and the authors proved that the sequential vibration signals are useful for the motor faults detection. The permanent magnet motor is another type of motor which commonly used in our daily life. Demagnetization fault is one of the faults existing in permanent magnet motors. There are also some demagnetization diagnosis methods have been proposed [3,4], such as finite element analysis (FEA) and time-frequency analysis (TFA), but these methods are difficult to use for real-time analysis.

Due to the rising trend of the Industry 4.x, artificial intelligence (AI) technology will rapidly boost applications through AR, and even Mixed Reality (MR), which will promptly increase the various types of services that AI technology can provide. At present, the development trend of global science and technology is moving in the direction of large data volume, high-speed communication, and reduced service delay. The key technologies of AR are developing towards various applications as well [5].

In addition, machine learning is the key to the next industrial revolution, and it can be used for motor fault diagnosis effectively. Machine learning can replace routine operations and the use of machine learning technology can instantly monitor equipment and predict maintenance needs [6, 7]. It no longer depends on traditional maintenance schedules and lots of management costs. Using a large amount of sensor data in this way has a good help on the device’s operating status and maintenance costs. The machine learning technologies can help to analyze and predict the possible faults of electric motors accurately.

The proposed method is applied to prevent the fault occur for higher power or permanent magnet motors, and combines the AR technology to provide the innovative application for users. The intelligent diagnosis system uses the time-recurrent LSTM neural network model [8, 9] to establish an electric motor health diagnostic model. Based on the differences between the parameters such as the vibration, voltage, temperature, and flux linkage collected during the electric motor operating and the predicted response of the diagnostic model to determine whether the current system and the initial health state are in good agreement. The intelligent diagnosis system also uses cloud data server to monitor and predict the health and potential faults of motors, which provides a more convenient and efficient management and maintenance mechanism, and presents the combination of reality and virtualization operating experiences.

2. Machine Learning and Augmented Reality

2.1 Machine Learning

Machine learning uses multiple disciplines such as probability theory, statistics, approximation theory, convex analysis, and computing theory to allow machines to "learn" to deal with specific problems automatically, and to automatically analyze from a large amount of data to find the regularity and use the regularity of the data to predict the future. Among them, the emergence of deep learning technology has accelerated artificial intelligence from perception to cognition, and has promoted the development of the entire artificial intelligence industry. Deep neural networks are currently the most common deep learning models, including many different types of networks, such as: Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Belief Networks (DBN), etc. Among them, CNN is suitable for image recognition, or the problem is transformed into a similar form; RNN is suitable for sequence to sequence translation, including converting speech to text or translating different languages. RNN is a very powerful dynamic system, but due to the problem of gradient disappearance / explosion, it is restricted to solve the problem of long-term dependence effectively. To solve this problem, the LSTM model with special implicit units is proposed [10].

LSTM is a kind of time-recurrent neural network, and its unique design structure is suitable for processing and predicting longer and more delayed events in time series. The LSTM contains a special unit called a memory cell that is used to memorize values of varying lengths of time, similar to accumulators and control neurons. LSTM has been proven to perform better than traditional RNN in speech recognition and machine translation applications [11]. The main difference between RNN and LSTM is that there is a message conveyor called cell state at the top of LSTM, which is actually the place of information memory. Certainly, the conveyor is unable to determine what information to be added or deleted by itself, but through the structure called control gates. LSTM network has three control gates: forget gate, input gate and output gate respectively. These three control gates confirm the feasibility of using gradient-based optimization methods and avoid the diffusion and explosion of gradient.

2.2 Augmented Reality

Industry and academia in various countries around the world have invested in AR research [12] and development for many years. AR and the Internet of Things (IoT), AI, cloud computing, big data, etc. are ranked as the most popular topics of information technology. Those applications extend to food, clothing, housing, transportation, education, music, medical, disaster prevention, etc. How industry experts turning requirements into specifications, designs, and manufacturing industry-compliant applications remains an innovative challenge.

AR consists of technologies that combine the real world and virtual goods, and allows users to use actual applications and system interaction in the real environment. This will increase user focus and motivation. AR is mainly used to detect the user's 3D spatial position in terms of visual presentation, and then to make a corresponding visual representation of virtual and real objects [13]. One of the most important technologies is spatial 3D positioning. Some researches proposed the 3D graphic display technologies [14], and to combine the virtual objects with 2D or 3D images. Precise spatial 3D positioning displays the pre-completed AR information on the device, and generates a virtual and real picture through visual overlay effects.

The technology of AR is to display some digital information on the display device and combine digital information with reality through vision. These information must have basic functions such as zooming in or out, so the information must be digitally modularized and created 3D spatial data reference points, so that the augmented reality display can be completed through 3D environmental detection during back-end display. 3D modeling is the most important technology for digitizing information or objects and 3D modularization. It can be achieved by infrared depth photography scanning or multi-lens photography acquisition. The AR technology provides a 3D virtual object with oblique viewing angles and the real-world scene, which can experience the combination of reality and virtualization during the interactive operation.

3. The Diagnosis System Design

The intelligent diagnosis system uses the LSTM model to establish an electric motor health diagnostic model. Based on the differences of motor parameters between the current motor operating status and the predicted response of the diagnostic model to determine whether the motor is healthy or not. Similarity is used as the basis for judging if the electric motor may appear malfunction. The accelerometer sensors are developed on each component of motors, and the operational status data are corrected by diagnosis platform through CAN (Controller Area Network) bus or Bluetooth interfaces. These data such as vibration, voltage, and flux linkage are provided to the motor diagnosis model to analyze and predict the healthy status of the motor. Tow hidden layers with LSTM are chosen in our diagnosis model.

The algorithm of the proposed diagnostic model has three main steps: data augmentation, model training, and evaluation. In the first step, the purpose of data augmentation is to reduce computation time and improve the convergence speed. The second step is training the diagnosis model with training dataset. The third step is validating the model with testing dataset, and the accuracy of prediction is the important evaluation index.

When the motor diagnostic model is chosen, the key problem is how to decide the parameters of input layers and output layers for LSTM model. The variable speed transmission system can be referred to the motor diagnostic model. The transmission medium of variable speed transmission system is power, and the system has an obvious vibration reaction. In order to discuss the vibration behavior effectively, the limited main degrees of freedom is supposed to descript the dynamic behavior of structural system. The motion equation can be defined as eq. (1).

$$M\ddot{x} + C\dot{x} + Kx = f$$

the parameter M, C and K represents as mass matrix, damping matrix and stiffness matrix respectively; x is displacement vector, and f is external force vector.

Eq. (1) is a description model of mechanical vibration system, and the model can be descripted according to the parameters such as: displacement, velocity and acceleration. Unfortunately, the displacement, velocity and acceleration parameters are unable captured at the same measurement node at the same time. To solve the problem, the centered difference scheme is applied as eq. (2).

$$\begin{cases} X_{t+\Delta t} = X_t + \dot{X}_t \Delta t + \frac{1}{2!}\ddot{X}_t \Delta t^2 \\ X_{t-\Delta t} = X_t - \dot{X}_t \Delta t + \frac{1}{2!}\ddot{X}_t \Delta t^2 \end{cases} \Rightarrow \begin{cases} \dot{X}_t = \frac{X_{t+\Delta t} - X_{t-\Delta t}}{2\Delta t} \\ \ddot{X}_t = \frac{X_{t+\Delta t} - 2X_t + X_{t-\Delta t}}{\Delta t^2} \end{cases}$$

and then we can get eq. (3) according to the eqs. (1) and (2):

$$\left(\frac{M}{\Delta t^2} + \frac{C}{2\Delta t}\right) X_{t+\Delta t} + \left(\frac{2M}{\Delta t^2} + K\right) X_t + \left(\frac{M}{\Delta t^2} - \frac{C}{2\Delta t}\right) X_{t-\Delta t} = f_t$$

To measure the displacement response, it requires a motionless reference point, and one observation parameter is needed to describe the function. The acceleration parameter is applied to describe this system. Therefore, find the second derivative of time for centered difference eq. (2), and we can get the eq. (4).

$$\left(\frac{M}{\Delta t^2} + \frac{C}{2\Delta t}\right) \ddot{X}_{t+\Delta t} + \left(\frac{2M}{\Delta t^2} + K\right) \ddot{X}_t + \left(\frac{M}{\Delta t^2} - \frac{C}{2\Delta t}\right) \ddot{X}_{t-\Delta t} = \frac{f_{t+\Delta t} - f_{t-\Delta t}}{2\Delta t} \tag{4}$$

by simplifying the eq. (4), it will get the time series model as eq. (5). The values of Φ_1, Φ_2, Θ_0 and Θ_2 are calculated as eq. (6).

$$\ddot{X}_t = \Phi_1 \ddot{X}_{t-\Delta t} + \Phi_2 \ddot{X}_{t-2\Delta t} + \Theta_0 f_t + \Theta_2 f_{t-2\Delta t}, \tag{5}$$

$$\begin{cases} \Phi_1 = -\left(\frac{M}{\Delta t^2} + \frac{C}{2\Delta t}\right)^{-1} \left(\frac{2M}{\Delta t^2} + K\right) & \Phi_2 = -\left(\frac{M}{\Delta t^2} + \frac{C}{2\Delta t}\right)^{-1} \left(\frac{M}{\Delta t^2} - \frac{C}{2\Delta t}\right) \\ \Theta_0 = \frac{1}{2\Delta t}\left(\frac{M}{\Delta t^2} - \frac{C}{2\Delta t}\right)^{-1} & \Theta_2 = \frac{-}{2\Delta t}\left(\frac{M}{\Delta t^2} + \frac{C}{2\Delta t}\right)^{-1} \end{cases} \tag{6}$$

The eq. (5) is the autoregressive exogenous (ARX) time series model. In this model, the current time responses are outputs, and the external interference at current time and previous time are inputs. The inputs and outputs of the time series model can be applied as the input layer and output layer of LSTM neural network. The prediction model for acceleration response can be built up according to the neural network architecture [15, 16]. By comparing the actual measured response with the predicted response, the degree of difference between the current state of the system and the initial health state can be obtained. If the degree of difference exceeds the alert value, determine that the system is in an unhealthy state. We can use roots mean square error (RMSE) to quantify the degree of difference between the current state and the initial state of the system, the estimation function is represented as eq. (7).

$$\sum_{\underline{n}=1}^{n} \sum_{\underline{\zeta}=1}^{\zeta} \left[a_{\underline{\zeta}}(t+\underline{n}\Delta t) - \underline{a}_{\underline{\zeta}}(t+\underline{n}\Delta t)\right]^2 \tag{7}$$

$a_{\underline{\zeta}}(t+\underline{n}\Delta t)$ indicates the actual measured response, and $\underline{a}_{\underline{\zeta}}(t+\underline{n}\Delta t)$ indicates the predicted response of the system. The architecture of LSTM neural network for system response prediction is shown as figure 1.

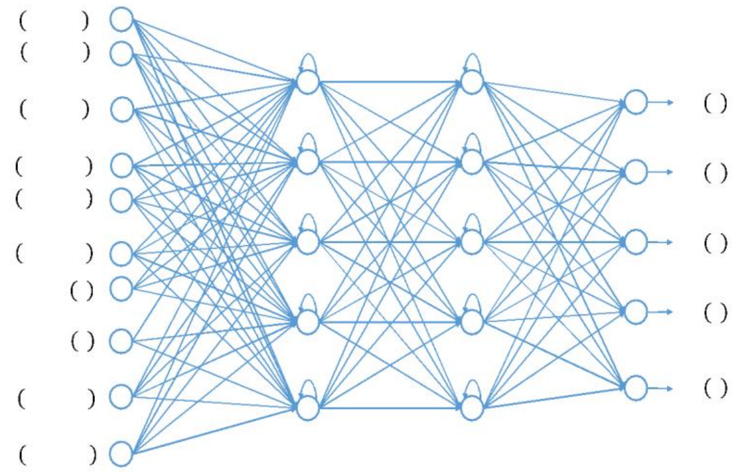

Figure 1: The LSTM neural network for system response prediction

The model for predicting motor current response based on the data of current, voltage, speed, etc. can be established according to the LSTM neural network. The LSTM neural network of electrical response can be constructed by substituting the input and output values determined by this model. And then compare the current response obtained from this model with the actual current data, it can determine whether the magnetic characteristics of the motor have made a difference or not.

Since the demagnetization of the motor is an irreversible chronic deterioration phenomenon, it is not easy to verify the actual data collected by the actual motor. If the data is generated by finite element analysis software, the results are not easy to accept. Therefore, through the hardware-in-the-loop system (HIL), the working condition of the real motor is simulated online, and the magnetic health state of the motor is adjusted in real time by changing the parameters of the operating interface. And then upload the data to cloud server for modeling and analysis.

All samples for the experiment will be represented the health conditions with length 256 and each condition has 1680 samples, in which 1344 samples are randomly selected for the training dataset, and the rest 336 samples are for the testing dataset. There are 256 units for the input layer of LSTM model, and 64 units for the first hidden layer of LSTM, and 32 units for the second hidden layer of LSTM. A max iteration value is set as 80, but if the loss of training dataset is still minor changing after a few iterations, the training phase will be ended. The accuracy rate represents the effectiveness of the diagnosis model, and the accuracy rate is the number of correct prediction divided by total number of dataset. The accuracy of fault prediction is up to 90%. The training phase is convergence after about 48 iterations, which proves it can reduce the training time and get a good result.

The proposed health diagnosis method provides the prediction of abnormal vibration and demagnetization for electric motors. The diagnosis model can be applied to the higher power and permanent magnet motors. The permanent magnet motors not only shows the difference caused by motor demagnetization, but it also demonstrates that the degree of demagnetization is positively correlated with the amount of difference. Therefore, this motor demagnetization diagnosis method can indeed present the health status of the permanent magnet motors.

4. The Augmented Reality Application Design

The motor 3D AR display application is developed with Unity software on mobile device platform. Unity is a cross-platform 2D/3D game engine developed by Unity Technologies. It can be used to develop stand-alone games for Windows, MacOS and Linux platforms, including iOS, Android Games or programs on mobile devices. The platform supported by Unity also extends to the HTML5 web platform based on WebGL technology. Using Unity 3D enabled several visual improvements. The graphical expression of the augmented objects became more precise by using Unity's built in shades.

Vuforia AR development tools have been added to the new version as a unified workflow across AR devices to provide customized resources that turn immersive vision into reality. Vuforia is a set of software development tool from Qualcomm for mobile device augmented reality applications, which provide good augmented reality development tools for mobile devices. It allows developers to place virtual objects through the camera viewfinder and adjust the position of objects on the solid background in front of the camera. This facility enables the user to place and position virtual objects and 3D models in reference with the target image so that when observed through a mobile device camera, the virtual object finds its oriented place on the reference image hence making itself appear as a part of the real scene.

Figure 2 illustrates the schematics of electric motor AR diagnosis system on mobile device. In addition to maintaining the necessary parameters generated by the electric motor design, the cloud AI computing server writes relevant data generated by the operation of the electric motor into the database, including the speed, voltage, vibration, temperature, and flux linkage, etc. of the electric motor. Then, AI computing module executes the fault prediction for electric motors, and the results are transmitted to the application program on the mobile device. The AR program on the mobile device displays the operating status of the electric motor. After obtaining the electric motor-related parameters on the server, the operating status of the AR electric motor model is displayed on the screen. And the information such as the operation, execution of the motor module, or setting of the motor parameters is synchronously returned to the server. By updating the database, and sending information back to the electric motor controller to set the operating parameters of the motor.

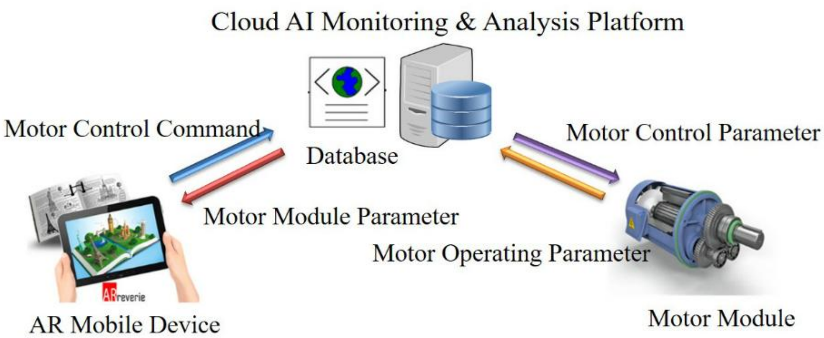

Figure 2: Architecture of the diagnosis system

The augmented reality application is developed on the mobile device platform, and the development of 3D electric motor modeling and the AR virtual object display are treated as the main axis. The augmented reality object display and user interactive operation combines with the motor design platform at the back-end cloud server. The back-end server controls the animation display of the rotation speed of the 3D electric motor model at the mobile device, allowing users to experience the 3D models and animations of various electric motor designs during the interactive operation.

The mobile device application is set to scan specific graphics to load the electric motor 3D module. This 3D electric motor model consists of several components, including a rotating shaft, a rotor, a stator, etc. These 3D motor components can be displayed or hidden by selecting from the program menu. The various components of the electric motor can be exploded or closed to see details of the electric motor model. The user not only can control the operation modes of the electric motor model to zoom in, zoom out, rotate up, down, left and right, etc. from the application interface, but also read the speed, voltage, temperature, and magnetic data from the cloud computing server to control the rotation speed of the electric motor model or display possible abnormal conditions.

If an abnormality is detected or a possible abnormal condition is predicted by the diagnosis system, the components of motor unit will appear different color in the application. For example, when the diagnosis system detects the rotor vibration is abnormal and the demagnetization phenomenon may occur, it sends the alarm message to the mobile device, and then shows the abnormal components with different color on the 3D motor models, which is shown in figure 3. Furthermore, the diagnosis system can be applied for the automotive system. The virtual components of automotive model can be displayed by scanning a car model.

Figure 3: The AR display of 3D electric motor model

The application on the mobile device has the ability to identify different modules of the electric motor and switch to the electric motor model to be simulated or monitored. The switching method can be used to load specific motor modules without image recognition, or use the screen menu to manually switch between different electric motor modules. The operating parameters of the electric motor model can also be set and controlled by the application, and then sent back to the database of the cloud server to update the electric motor status synchronously. It also allows users to experience 3D digital electric motor models and animations of various electric motor designs during the interactive process.

In terms of the electric motor design and industrial applications, using AR software to control the parameter design and operating status of motor equipment can improve the work flow and efficiency of staff inspection equipment. For example, the staff scans the AR device for the electric motor to be measured, and then reads the operating parameters of the electric motor from the cloud server, and displays the relevant information through AR. The data will be sent back to the cloud server system to set the operating status of the electric motor synchronously. Based on accumulated data on the cloud server and machine learning technology, the system can determine the status of this equipment is abnormal or not, and display early warning to reduce the risk of equipment failure.

5. Conclusion

This research provides an intelligent diagnosis system which integrates the augmented reality technology for the electric motors. The integration of AR system and AI cloud platform is developed to monitor operation conditions of the electric motor on the mobile devices. The intelligent diagnosis mechanism of electric motors applies LSTM machine learning algorithms to establish the motor health diagnostic model. By combing with cloud data management and machine learning technologies, an AI cloud platform is developed to predict the health status and detect possible abnormalities of the electric motor. The AR technology can also displays the alarm signals of the digital electric motor model on the mobile devices immediately to provide a more convenient and efficient management mechanism. Users can connect to the AI cloud server through their mobile devices to analyze and monitor the 3D electric motor modules at any time with a more intuitive and friendly operation interface, and experience the combination of reality and virtualization during the interactive operation.

In the future, we will enhance the diagnosis system for electric motors, and compare with various machine learning algorithms to get the better diagnosis model and improve the accuracy of prediction results. Besides, the AR display system will scan the real solid motors and vehicles to display virtual information on a real object, and provides real intuitive interactions for users.

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