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A Data Fusion Method of Locomotive Multi-source Axis Temperature Using Bayes Theorem

[1]He De-Qiang, [2]Liu Qi-Yang, [1]Liu De-Chang, [3]Yao Xiao-Yang and [1]Chen Er-Heng
[1]School of Mechanical Engineering, Guangxi University, Guangxi, 530004, Nanning, China
[2]Department of Science and Technology, Guangxi University, Guangxi, 530004, Nanning, China
[3]Zhuzhou CSR Times Electric Co., Ltd, Hunan, 412001, Zhuzhou, China

Abstract: The axis temperature online detection and maintenance is one of the most important components in railway systems and rolling stock remote condition monitoring system. This study will focus on the data fusion method of locomotive multi-source axis temperature using the Bayes theorem, which analysis how to obtain locomotive axle temperature status data, search the abnormal axle temperature mutation data, axle temperature data fusion and transmission. This method will provide more accurate axle temperature data, axle temperature alarm and locomotive remote collaborative troubleshooting technical support. It has been used in the China Locomotive remote monitoring and diagnosis system, which can improve locomotive utilization, reduce locomotive dwell and idle times and improve crew productivity.

Key words: Bayes theorem, axis temperature, locomotive, data fusion method

INTRODUCTION

Locomotive axles are safety-critical components, when an axle breaks there is a high risk of derailment with potentially disastrous consequences. In order to maintain the locomotive safety, a large number of investigations and experiments have been carried out by outstanding research ever since and many improvements have been made in the material, manufacturing, heat treatment and design method. Axles in service are regularly checked by ultrasonic testing and magnetic particle inspection (McQuaid and Jones, 1999; Hirakawa *et al*., 1998; Makino *et al*., 2011).

A common reason of axle failures is overheating of bearings ("hot box" failure). With the continuous improvement of train speed, locomotive remote fault diagnosis and maintenance becomes increasingly important, the axis temperature online detection and maintenance is one of most important components for locomotive remote fault diagnosis. In order to improve intelligent maintenance level of the existing locomotive axis temperature detection, besides improving equipment management level and increasing the service life of onboard parts, it also need to enhance the remote condition monitoring and fault diagnosis technology of locomotive axis temperature.

At the beginning of the development of railway informatization, the detection and maintenance of the drive shaft was done by technicians who can do some detection through watching, touching, hearing and using simple instruments for the shafts, bearings and so on after the locomotive had berthed. Once abnormal, it need to be removed immediately and sent to maintenance workshop for further repairs or maintenances. This method of detection and maintenance contains heavy workloads, many human factors, great errors and it is a kind of the backward state of locomotive axle box detection means (Smith and Hillniansen, 2004; Zerbst *et al*., 2005).

Now, there are three main ways for locomotive axle box detection and fault diagnosis: local online maintenance; warehousing inspection; remote and intelligent maintenance online. The first way of detection and maintenance includes collect real-time status signal of each position within the axle box through axis temperature detection equipment and photoelectric sensors installed on opposite ends of the shaft. Then, the processed information is sent to the cab screen which can be viewed that shows current status information and dealing options and the drivers can implement the related processing according to the prompt messages. However, the driver is limited to perform the repair work as the locomotive is still running. The second way of detection and maintenance is that the maintenance team can do some works for axle box after the locomotive parked. Generally, the first step is to do internal inspection for axle box by the instrument, which is called minor repairs, it is only when a fault is found then the axle box will be removed from the locomotive and moved into the repair workshop, which takes considerable time, human and financial resources, leading to the decrease of locomotive utilization. The third way is online remote intelligent maintenance, which collects the status signal online of axis positions from

Corresponding Author: He De-Qiang, School of Mechanical Engineering, Guangxi University, Guangxi, 530004, Nanning, China

each axle box by sensor and deals with the collected status signal by related equipments, then, real-time transmits to the GCC (Ground Control Center). The expert group on the GCC performs the fault diagnosis tasks, the final diagnosis result feedback to the locomotive, which drives the related equipments to implement troubleshooting and maintenance. The advantage of this method is that it transmits real-time information to the GCC, so that staff on the GCC can deal with the fault diagnosis and maintenance of locomotives. However, state signal acquisition and transmission is inevitably affected by external interference. As a result, collected data has some uncertainties, especially the axis temperature data as an important source of axle box fault diagnosis, which will directly affect the result of axle box fault diagnosis. Therefore, the locomotive axle temperature data processing is a key link in the process of axle box online detection and fault diagnosis (Gerdun *et al*., 2007; Zerbst *et al*., 2013; Yasniy *et al*., 2013).

This study is organized in the following order. Section 2, 3, 4 and 5, respectively introduce the data fusion method of locomotive multi-source axis temperature using the Bayes theorem, which includes how to obtain status data of locomotive axle temperature, search the abnormal data of axle temperature, axle temperature data fusion and transmission, to be concluded in Section 6.

OBTAINING STATE DATA OF LOCOMOTIVE AXLE TEMPERATURE

The GCC of locomotive remote collaborative fault diagnosis system communicates with the onboard detection and diagnosis system through Win Socket and receives real-time online locomotive axle temperature state data, which searches the axle temperature mutation data by context comparison method. First, it takes mutation probability values instead of the prior probability of false alarm axle temperature state data and calculates the posterior probability based on the Bayes theorem. Then, it performs the next iteration when receiving the next set of data and calculates its joint conditional probability. The multi-source axle temperature data are divided into two types according to a lot of independent and non-independent sensors and it will cycle forward until the posterior probability maximum is obtained and take a set of the maximum posterior probability as the axle temperature excessive theoretical value. Finally, it will show the axle temperature real-timely by using the AJAX, Javascript and XML technology and give an alarm diagrams of axle temperature state. This method can effectively reduce the error rate of locomotive multi-source axle temperature data and the number of false alarms and provide staffs with a low error rate of axle temperature data and accurate axle temperature alarm information.

Creating a remote socket: The TCP socket is bound to a fixed IP address through using integrated asynchronous TCP socket communications technology and the port is defined 99, the communication protocols will use the TCP/IP. It will run the port monitoring after the system startup and establish a remote connection when listening to the onboard system connection request. Then, it will ready to receive axle temperature data and loop to receive locomotive axle temperature data. If the connection is broken, the system will loop to listen for new connections by using heartbeat technology. The key codes show as follows:

```
Thread getdataThread =new
Thread(newthreadStart(get3GdataOperate.Start Listening));
getdataThread.Start();
public static string commandStr ="SERVER+SOCKET= WORKING";
public static void StartListening();
private static void AcceptCallback(IAsyncResult ar);
private static void ReadCallback(IAsyncResult ar);
```

Reading the data from the socket: Firstly, the state of thread is set to "occlusion" so as to avoid data conflicts between the next frame and current frame and the setting method is as follows:

```
StateObject mystate = (StateObject)ar.AsyncState;
mystate.receiveDone.Set();
```

Then, there will creat a new socket for receiving data and inheriting the listening sockets and reading the data. The key codes show as follows:

```
Socket handler = mystate.workSocket;
 if (mystate.buffer.Length > 0)
 {
 currentbytes = new byte[mystate.buffer.Length];
 for (int i = 0; i < mystate.buffer.Length; i++)
 {
 currentbytes[i] = Convert.ToByte(mystate.buffer[i]);
 }// If there are any unreceived data
 if (handler.Available > 0)
 {
 StateObject leftstate = new StateObject();
 leftstate.buffer = new byte[handler.Available];
 leftstate.workSocket = handler;
handler.BeginReceive(leftstate.buffer, 0, handler.
Available,SocketFlags.None,newAsyncCallback(Read Callback), leftstate);
 leftstate.receiveDone.WaitOne();
 }
```

Determining the validity of axle temperature data: Through the parity bits of each frame axle temperature data to judge the validity of data, the check data is the complement of the sum of all bytes in this frame data according to the predefined data protocol format. The data is only valid when the data frames in accordance with above format, otherwise will be blocked. Finally, the valid

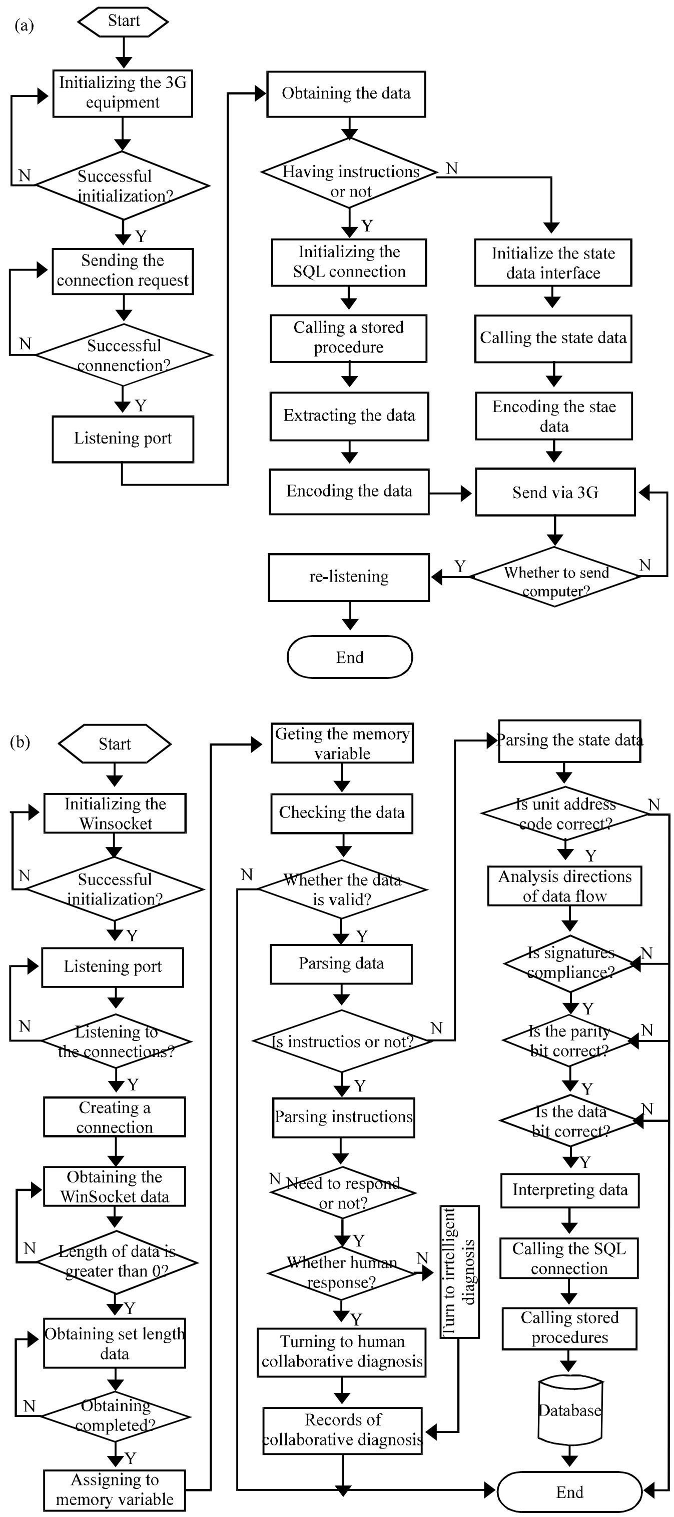

Fig. 1: Data acquisition and transmission processing flow chart of locomotive multi-source axle temperature, (a) Locomotive axle temperature data collection, (b) Receive the temperature data on ground control center

locomotive status data is be assigned be dynamic memory variables. The data acquisition and transmission processing flow chart of locomotive multi-source axle temperature is shown in Fig. 1.

SEARCHING THE ABNORMAL AXLE TEMPERATURE DATA

The axle temperature mutation data is search through the context comparison method. The algorithm is as follows: The continuous 2n group of axle temperature data will be stored in the array Temp1 and Temp2 which have n storage capacity and head-tail connection. The relatively new set of data is stored in Temp1 and recently received axle temperature data is stored Temp[n]. Then the latest axle temperature data is assigned to the variable curTemp. If the value of curTemp-Temp1[n] is greater than the maximum measured temperature value that locomotive axle temperature sensor can accepted, the curTemp is a abnormal data. The Temp1 is assigned to Temp2, then the Temp1 will receive the next set of data and the recent axle temperature data is updated to the curTemp. Comparing the each data between curTemp and Temp1, if the difference is greater than the maximum measured temperature value of locomotive axle temperature sensor can accepted, the calculator is adding one until the end of the match. If the statistical data of calculator is greater than n/2, the mutation data is assigned to the Temp1[n] -Temp2[n]. If the mutation data is small, the Temp1 is garbled and be blocked. It will continue to receive the next set of data until find the axle temperature mutation data. The algorithm logic flowchart of locomotive multi-source axle temperature mutation data is shown in Fig. 2.

AXLE TEMPERATURE DATA FUSION

In order to correctly use the Bayes theorem to reduce the uncertainty of axle temperature data, it need to obtain the correct prior probability of axle temperature data. Assume the probability of the *k* frame axle temperature mutation data is P (X_1|X), P (X_2|X),..., P (X_i|X) and the conditional probability of correct axle temperature data are (1-P (X_1|X)), (1-P (X_2|X)), ..., (1-P (X_i|X)). When the system receives the axle temperature data of next frame (the k+1 frame), follow these steps for processing:

- Calculate the posterior probability P (X_1|X), P(X_2|X), ..., P (X_i|X) of the true value X through using the Bayes equation:

$$P(X|X_i)=\frac{P(X_i|X)P(X)}{\sum_Y P(X_i|Y)P(Y)}.$$

- Take the posterior probability P (X_1|X), P (X_2|X), ..., P (X_i|X) to instead of the prior probability P (X_1), P (X_2), ..., P (X)
- If the sensors are independent for each other:

$$P(X|X_1,X_2,\cdots,X_i)=\frac{P(X)\cdot\prod_{j=1}^{i}P(X_j|X)}{\prod_{j=1}^{i}P(X_j)}.$$

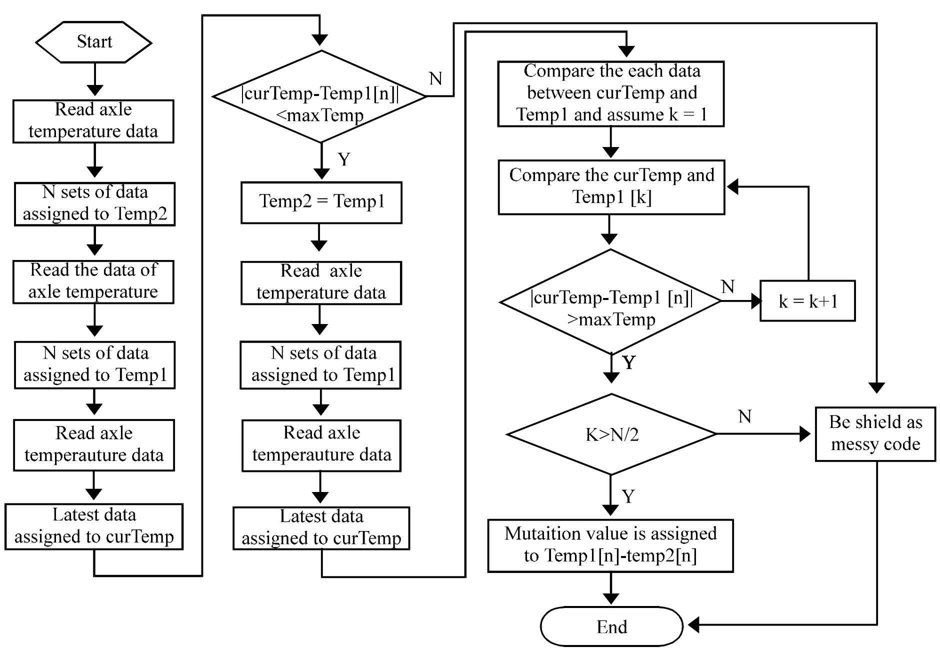

Fig. 2: Algorithm logic flowchart of locomotive multi-source axle temperature mutation data

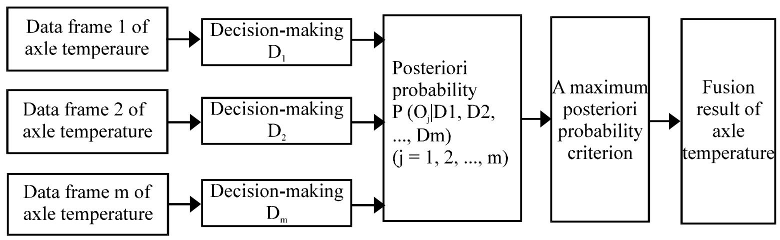

Fig. 3: Data fusion processed flowchart of locomotive multi-source axis temperature

4) Else:

$$P(X|X_1,X_2,\cdots,X_i)=\frac{P(X)\cdot\prod_{j=1}^{i}P(X_j|X)}{\prod_{j=1}^{i}P(X_j)\cdot\prod_{j=1}^{i}P(X_j|X)}$$

- Cycle the above calculation until P $(X|X_1, X_2,\ldots,X_i)$ less than the predetermined accuracy
- Take the largest axle temperature data frame of posterior probability to storage or transmission for calling. The data fusion processed flowchart of locomotive multi-source axis temperature is showing in Fig. 3

Finally, the axle temperature will be real-time show on screen of the GCC by the AJAX, Javascript and XML technology and give the alarm diagrams of axle temperature state. It will provide staffs with a low error rate axle temperature data and accurate axle temperature alarm.

AXLE TEMPERATURE DATA TRANSMISSION

The axle temperature data after the fusion processed include the real-time and static axle temperature data. Real-time dynamic data is stored in the memory variable and it can be obtained directly through the background page, the background data is assigned to user variables when the user page download is complete. The static axle temperature data is stored in the database and it need to create a separate interface to connect the database. The static axle temperature data will be obtained through the character instruction or calling stored procedure, then, the data will be transferred to a Web page by using AJAX object.

Alarm processing of axle temperature: The state of axle temperature is divided into presence or no sensor, with or without alarm, over temperature, heating, normal temperature and so on and be displayed with different icons. The system calls background function to analyze the axle temperature data when the user interface page receives the new axle temperature data and determines the corresponding axle temperature state. Then, it will assign the result to the user variables and refresh the axle temperature alarm figures.

Data processing of uniaxial temperature: The uniaxial temperature state is set to hidden layer and it is associate with the axle temperature alarm icons. The system will refresh the axle temperature map and the hidden layer of uniaxial temperature state when the user page receives the new axle temperature data.

CONCLUSION

To maintain the safety record of railway systems, much effort has been paid to improve the axle detection. As stated, the safety of the railway has been ensured by maintenance, such as regular axle temperature inspection. This method can achieve the fusion processing of locomotive multi-source axle temperature data using data fusion technology based on the Bayes theorem, which can extract the axle temperature mutation data when the axle temperature data is ensured undistorted and take the mutation rate as the excessive prior probability of axle temperature. Then, it need to cycle forward and calculate the accurate axle temperature exceeded values by using the Bayes theorem and the purpose of this action is reduce the number of false axle temperature alarms. It will provide staffs with more accurate axle temperature data, axle temperature alarm and locomotive remote collaborative troubleshooting technical support. The data fusion method has been used in the China Locomotive Remote Monitoring and Diagnosis System.

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