Research on Fault Detection Method of Mineral Powder Production Line Based on Information Fusion

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Abstract. By analysing the uncertainty of information in the production process of the mine, and the diversity of the fault detection components of the production equipment. Combining the trend of big data development, comparing and analysing various fault diagnosis methods, a Bayesian information fusion algorithm based on improved learning process is proposed. The traditional Bayesian information fusion algorithm is combined with the learning idea of migration algorithm to obtain an optimized Bayesian fault detection algorithm. This algorithm can minimize the waste and loss of data and improve the detection accuracy.

1. Introduction
The rare earth ore powder production line has different characteristics from other mineral processing production lines. There are many electromechanical devices on one line, the failure in a certain place may cause the whole line production to be affected. It is difficult to effectively monitor the faults. At the same time, the work of a large number of electromechanical devices is status can also provide information to reflect the fault status of the production line. Such as the current and voltage changes of the power unit, the various operations of the transmission: the slip and break of the belt, etc., there are complex interconnections, different fault information and corresponding fault detection signals are different, how the fault detection signal can be detected in advance is a prediction problem based on multiple influencing factors, which is difficult to describe by analytical methods. The widespread application of intelligent fault detection algorithms provides an effective way, that solution the problem. Literature [1] proposes a grid fault monitoring method based on switching quantity and multi-source information fusion, it aims to solve the blackout caused by the refusal and mis-operation of various components of the power system, and improve the accuracy of diagnosis and have a good effect. Literature [2], by constructing the switching function, a multi-group genetic algorithm is introduced for the premature convergence problem of genetic algorithm, which locates the fault segment of the distributed power distribution network accurately, improves the diagnostic efficiency, and has good validity and fault tolerance. The effectiveness and accuracy of the method. Most of these studies use a combination of two or more different algorithms to achieve effective detection. Based on the existing Bayesian algorithm, this paper proposes a new improved method, by changing the
2. **Overall design of fault detection**

Defining each fault type $FT_i$: For the voltage of a three-phase motor, the voltage is usually in the range of $380\pm 5\%$ during normal operation, when the voltage is not in this range, the voltage is abnormal, which may cause some kind of motor failure. The transmission device is connected by a transmission belt, and by detecting the belt speed of the transmission belt, it is judged that the transmission belt is slipped or broken. The eigenvector corresponding to each type of fault definition $X_1, X_2, \ldots, X_n$.

A training sample is established, and the fault feature is determined by extracting the feature vector to establish a fault diagnosis model. Combined with the Bayesian principle, the mean and variance of each feature are calculated, and a preliminary judgment is made. For the data that judges the error, add to the new data, combine the migration learning ideas, construct a closed-loop learning system, re-iterate, correct the fault diagnosis model, and improve the diagnostic accuracy by continuously updating the data[3].

3. **Bayesian algorithm based on improved learning strategy**

3.1 *Bayesian algorithm description*

The Bayesian algorithm is based on the concept of frequency in statistical methods and statistics. From the perspective of frequency, it is assumed that the data follows a certain distribution, and several key parameters of the distribution are calculated to obtain the established model. The Bayesian is modeled based on actual data of reasoning, the data required from actual collected by sample training, update the model estimates, so the results of a situation or events predicted. In Bayesian statistics, we use data to describe the model, instead of using the model to describe the data[6].

The Bayesian algorithm is mainly based on the Bayesian formula:

$$P(B_i|A) = \frac{P(AB_i)}{P(A)}$$

$$= \frac{P(B_i)P(A|B_i)}{\sum_{j=1}^{n} P(B_j)P(A|B_j)} i = 1, 2, \ldots, n$$

(1)

Assume that the training sample data is $S = \{S_1, S_2, \ldots, S_n\}$, for each set of sample data feature attribute is $X = \{X_1, X_2, \ldots, X_n\}$, the corresponding feature vector is $Y = \{Y_1, Y_2, \ldots, Y_n\}$, combined with
the sample feature attribute, the sample data is divided into $Y_m$ different categories, respectively represented by different feature vectors. $X$ and $Y$ represent random variables and follow the principle applied by Bayesian algorithm, that is, each component is independently and identically distributed.

Definition, $P(Y)$ is the $Y$ prior probability; $P(X)$ is the attribute set probability; $P(X|Y)$ is the conditional probability; $P(Y|X)$ is the posterior probability of $Y$, which can be expressed as:

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

(2)

According to equation (2), the Bayesian formula can be generalized as:

$$P(X|Y = y) = \prod_{i=1}^{d} P(X_i|Y = y)$$

(3)

Combining the formula (2) and the formula (3), under the condition of given feature attribute probability, it is assumed that the applicable principle is established, for a specific failure probability, according to the conditional probability $P(X|Y)$, the posterior probability can be calculated:

$$P(Y|X) = \frac{P(Y)\prod_{i=1}^{d} P(X_i|Y)}{P(X)}$$

(4)

Through the posterior probability, it is estimated whether the data belongs to this type of fault, thereby achieving a classification effect. Since the prior probability is fixed, for the comparison of the posterior probability, we only need to compare the relative sizes of the molecules, namely:

$$Y_{\text{max}} = \arg \max P(Y|X) = \arg \max P(Y)\prod_{i=1}^{d} P(X_i|Y)$$

(5)

Combining the above process, we can conclude that the Bayesian algorithm estimates the training model under the condition of fixed training samples, the algorithm process is relatively simple and the estimation efficiency is high; Similarly, this also causes data waste, the training model is fixed, and is affected by the size of the training sample data set.

3.2 Bayesian algorithm for improving learning strategies

Combined with the characteristics of Bayesian algorithm, on the basis of Bayesian algorithm learning, the learning system is improved, the learning ability is enhanced, and the accuracy of fault detection is improved. Through the extracted fault feature vector $X_i$, all the data are classified according to the classification standard to form a fault feature attribute set $FT = \{FT_i | i = 1, 2, \cdots \}$, and a fault detection model is formed by the Bayesian algorithm, and the diagnosis result is output. For the error detection result, the error data is returned to the feature extraction part, the classification is re-classified, the fault detection model is re-modified, and finally a total output result is given.
3.3 Improved Bayesian algorithm model

Combined with a company's rare earth ore production line, as shown in Figure 3.

Figure 3. Rare earth extraction production line

Real-time voltage and speed are detected by speed sensor and voltage sensor to form a training sample \( S = \{S_1, S_2, \cdots, S_n\} \), preliminary data classification to form fault characteristics \( FT = \{FT_i | i = 1, 2, \cdots\} \), define the corresponding fault eigenvector \( X_1, X_2, \cdots X_n \), estimate model parameters to form a test model; test the test sample data to extract the posterior probability \( P_t \) of the preliminary test, set the probability limit for data migration to 0.5, when \( P_t \geq 0.5 \), explain that the detection effect is good, and the test results are output; Otherwise, return to closed-loop learning system, the data is re-detected, the detection model is modified, and the number of iterations is set until the posterior probability converges, when the maximum number of iterations is reached, if it still does not converge, the optimal value is selected, otherwise, the initial model output; the output result is calculated from the mobility \( \varepsilon \) of the initial detection, and the detection effect is evaluated.

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\varepsilon = \frac{p_t - p_m}{p_t}
\]

4. Conclusion

This paper proposes a Bayesian fault detection algorithm based on improved learning strategy, by improving the learning strategy of Bayesian algorithm, the learning ability of the algorithm is increased, the data waste is reduced, the detection accuracy is improved, and the reliability of the detection result is improved. For the rare earth ore powder production line, the real-time data detected on the extraction and stirring device, through this method, the equipment operation status of the production workshop can be monitored in real time, the automation degree of the production workshop can be improved, and the labor cost can be reduced, thereby improving production efficiency and reducing production cost requirements.
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