Fault diagnosis of head sheaves based on vibration measurement and data mining method

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Abstract
Head sheaves are critical components in a mine hoisting system. It is inconvenient for workers to climb up to the high platform for overhaul and maintenance, and there is an urgent need for condition monitoring and fault diagnosis of head sheaves. In this article, Fault Tree Analysis is employed to investigate the faults of head sheaves, and headframe inclination, bearing faults, and head sheave swing are the three focal faults discussed. A test rig is built to simulate these three faults and collect vibration signals at bearing blocks. Based on vibration signals, some characteristic parameters are calculated, and together with the fault labels, a sample set is established. Before the selection of an excellent data mining method, these features are screened according to their significance, and then, gain–percentile chart, response–percentile chart, and prediction accuracy are used as the criteria to make a comparison between data mining algorithms. The result shows the boosted tree algorithm outperforms others and presents excellent performance on the evaluation of head sheave faults. Finally, this method is verified on a data set of 20 samples, and each case is identified correctly, which illustrates its high applicability.

Keywords
Mine hoist, head sheave, data mining, boosted tree, Fault Tree Analysis, feature selection

Introduction
A mine hoisting system is the equipment that conveys coal or other mineral resources from underground to the surface. No matter it is a winding hoist or a floor friction hoist, the head sheaves are always a critical component in the whole system.1 It is used to support and guide the hoisting wire ropes, as shown in Figure 1.

The malfunction of head sheaves might result in the failure of hoisting operation and even cause fateful accidents.2 The possible faults include sheave swing, headframe inclination, bearing faults, and so on. A head sheave platform is around dozens of meters high, as shown in Figure 2; so it is inconvenient for workers to examine and repair head sheaves, especially in extreme weather. Hence, it is of great significance to carry out research on online condition monitoring and fault diagnosis system of head sheaves for a hoisting system.3 In addition to climbing to the high platform to check head sheaves, some field engineers monitor real-time temperature of the bearings to get fault information, which is effective to predict the possible fault status according
to excessive high temperature; however, the identification of where the fault originates from is beyond the capability of temperature monitoring. Vibration monitoring can compensate for this deficiency, and scholars have done plenty of research in this area. For instance, Liu Y et al.\textsuperscript{4} carried out cepstrum analysis on vibration signal in fault diagnosis of bearings. During fault identification, data mining method begins to take an important role. Liu X et al.\textsuperscript{5} used extreme learning machine method in gear fault diagnosis. Gao Y et al.\textsuperscript{6} employed generative adversarial networks to detect bearing fault. Hence, for head sheaves, it is of great feasibility and significance to build an online fault diagnosis system.

However, in current research and field practice, faults of head sheaves have not been concluded and analyzed comparatively. What faults should be paid more attention to? What features should be selected? What algorithm outperforms others in the identification of head sheave faults? These are the key problems that this article focuses on. Fault Tree Analysis (FTA) is employed creatively to look into the head sheave faults systematically, and then, a data mining method is used to screen features based on their different contribution to fault identification. Finally, algorithms are compared to decide the most suitable one to give an ideal prediction.

**FTA of head sheaves**

Failure mechanism must be analyzed before health status is evaluated. FTA is an effective way to investigate and improve reliability and safety.\textsuperscript{7} The FTA for head sheaves is shown in Figure 3. Head sheave failure, whatever the cause is, is regarded as the top event $S$. Three intermediate events, headframe inclination $M_1$, excessive noise $M_2$, and excessive swing $M_3$, lead to the occurrence of the top event $S$. Headframe inclination can be caused by process defects $X_1$ and improper installation $X_2$ during construction period. Deviation of the conveyance $X_3$ or bearing faults $M_4$ may lead to excessive noise $M_2$. Excessive wear $X_4$, external impact $X_5$, serious crack $X_6$, and deformation $X_7$ are all causes to bearing faults $M_4$. Improper installation $X_2$ and uneven force of wire ropes $X_8$ might result in excessive swing of head sheaves.

Algebraic method is used to compute this fault tree,\textsuperscript{8} whose process is

$$S = M_1 + M_2 + M_3$$
$$= X_1X_2 + X_3 + M_4 + X_2 + X_8$$
$$= X_1X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_2 + X_8$$
$$= X_2 + X_3 + X_4 + X_5 + X_6 + X_7 + X_8$$

According to this result, the minimum cut set has been obtained, which is $X_2, X_3, X_4, X_5, X_6, X_7, X_8$. Their corresponding bottom events are improper installation, guide deviation, excessive wear, external impact, serious crack, deformation, and uneven force of wire ropes. Diagnosis of faults of conveyance guide has been researched by lots of scholars. For instance, Ma C et al. found valuable information from vibration signal
and realize the identification of various failure modes of rigid guide. Therefore, guide fault recognition is skipped in this article. Three failure modes, headframe inclination, bearing faults, and excessive swing of head sheaves, together with normal status, form the four patterns to be distinguished in the following part.

Construction of the test rig

With the increasing depth of mining, multi-rope winding hoist will be more and more widely applied in the near future, so a test rig of multi-rope winding hoisting system is built, as shown in Figure 4. It includes conveyances, wire ropes, head sheaves, torque sensor, drum, brake disk, gearbox, rotary encoder, bearing block, driving motor, and so on. The driving motor drives the winding drums through the gearbox. Conveyances are lifted and lowered by wire ropes, which pass through the head sheaves and wind around the drums. This test rig can simulate the three faults of the head sheaves. Some bolts of this rig can be adjusted to artificially make the faults of headframe inclination and head sheave swing. Bearing faults investigated in this article basically have the form of impact, so external impact force is applied on the bearing block to simulate the effect of bearing faults. Main technical parameters of this test rig are listed in Table 1.

Vibration signals have abundant fault information which is needed during the diagnosis, so vibration sensors in three directions are installed on the bearing block to collect vibration information. Figure 5 shows a segment of vibration signal and its fast Fourier transform (FFT) spectrum. Three faults have their different performance in vibration signals. To mine necessary fault information from these signals, some characteristic parameters are preselected, which include the maximum value, minimum value, mean value, standard deviation, root mean square error, peak-to-peak value, skewness, and kurtosis expressed as Max, Min, Mean, Std, RMSE, VPP, Skewness, and Kurtosis, respectively. For filtered vibration signals, a segment of 1 s forms one sequence $X$, with which the eight parameters are calculated. The skewness $\text{Skew}(X)$ and the kurtosis $\text{Kurt}(X)$ are defined as

![Figure 3. Fault Tree Analysis of head sheave.](image-url)

| Parameters                  | Value  |
|-----------------------------|--------|
| Headframe height            | 12 m   |
| Diameter of wire rope       | 12 mm  |
| Conveyance volume           | 0.3 m$^3$ |
| Drum diameter               | 300 mm |
| Main shaft power            | 4 kW   |
| Rated speed of main shaft   | 960 r/min |
| Maximum hoisting speed      | 0.5 m/s |

Table 1. Main technical parameters of the test rig.
Skew$(X) = E \left[ \left( \frac{X - \mu}{\sigma} \right)^3 \right] \quad (1)

Kurt(X) = E \left[ \left( \frac{X - \mu}{\sigma} \right)^4 \right] = \frac{E \left[ (X - \mu)^4 \right]}{\left( E \left[ (X - \mu)^2 \right] \right)^2} \quad (2)

where $\mu$ is the mean value and $\sigma$ the standard deviation.

After three faults are simulated on the test rig, corresponding vibration signals are collected and the statistical parameters are calculated to build the data set labeled with relevant failure modes or normal status. Part of this data set is listed in Table 2.
Table 2. Part of the data set of the collected vibration signals.

| Direction | Max  | Min   | Mean  | Std  | RMSE  | VPP  | Skewness | Kurtosis | Status     |
|-----------|------|-------|-------|------|-------|------|----------|----------|------------|
| x         | 6.44 | −8.54 | −0.94 | 5.30 | 5.38  | 14.98| −0.03    | −1.50    | Normal     |
| x         | 6.44 | −8.54 | −0.94 | 5.29 | 5.37  | 14.98| −0.03    | −1.50    | Normal     |
| y         | −13.68| −13.92| −13.82| 0.07 | 13.82 | 0.24 | 0.54     | −0.68    | Normal     |
| y         | −13.75| −14.17| 0.11  | 13.95| 0.42  | −0.05| −0.84    | Normal    | Normal     |
| z         | 6.59 | −8.47 | −0.83 | 5.32 | 5.38  | 15.06| −0.03    | −1.50    | Normal     |
| z         | 6.59 | −8.47 | −0.83 | 5.32 | 5.38  | 15.06| −0.03    | −1.50    | Normal     |
| x         | 6.60 | −8.64 | −0.91 | 5.38 | 5.46  | 15.25| −0.03    | −1.50    | Bearing failure |
| x         | 6.60 | −8.65 | −0.91 | 5.38 | 5.46  | 15.25| −0.03    | −1.50    | Bearing failure |

Max: maximum value; Min: minimum value; Std: standard deviation; RMSE: root mean square error; VPP: peak-to-peak value.

Feature selection

Feature selection can reduce the dimensionality of the data set, facilitate the data mining, and improve classification efficiency and accuracy. The chi-square test is used to screen the features here. For each feature \( f_i \), \( 1 \leq i \leq p \), \( p \) is the number of the features, the chi-square value between \( f_i \) and status \( (s_j, 1 \leq j \leq q, q \) is the number of the statuses) can be calculated by

\[
\chi(f_i, s_j) = \sum_{m=1}^{n} \frac{(f_{i-obs} - f_{i-exp})^2}{f_{i-exp}}
\]

where \( n \) is the number of samples and \( f_{i-obs} \) and \( f_{i-exp} \) are the observation value and expected value of feature \( f_i \), respectively.

For data set of multiple classes here, the importance of feature \( f_i \) can be measured by the maximum chi-square value of this feature to different statuses, that is

\[
\chi(f_i) = \max \{ \chi(f_i, s_j), 1 \leq q \}
\]

With feature selection algorithm in Statistica, the significance of each feature is calculated, which is listed in Table 3 and shown in Figure 6. According to their significance, five features whose chi-square values are larger than 17 are remained. From primary to secondary, they are RMSE, Min, VPP, Std, and Skewness.

Table 3. Feature significance.

| Feature   | Chi-square value |
|-----------|------------------|
| RMSE      | 49.33333         |
| Min       | 38.09524         |
| VPP       | 29.33333         |
| Std       | 29.33333         |
| Skewness  | 17.02222         |
| Kurtosis  | 12.78746         |
| Max       | 5.00000          |

Max: maximum value; Min: minimum value; Std: standard deviation; RMSE: root mean square error; VPP: peak-to-peak value.

Algorithm selection

Since there are variety of algorithms that can be employed to mine fault information, algorithm selection should be done to improve fault identification accuracy. Algorithms of boosted tree, K-nearest neighbor, Naive Bayes classification and support vector machine, and five neural networks are compared with gain chart, lift chart, and prediction accuracy as the criteria. Gain chart is the curve of gain with percentile, while lift chart is the curve of response with percentile. Gain, percentile, and response are defined as

\[
Gain = \frac{d}{a + b + c + d}
\]
Percentile \( = \frac{b + d}{a + b + c + d} \)  
Response \( = \frac{a}{b + d} \)  

where \( a \) is the number of the cases that are actually negative and predicted negative, \( b \) is the number of the cases that are actually negative and predicted positive, \( c \) is the number of the cases that are actually positive and predicted negative, and \( d \) is the number of the cases that are actually positive and predicted positive. Among the three fault patterns, head sheave swing is the most alarming problem, so gain–percentile and response–percentile charts on the identification of swing status are obtained and compared between different algorithms, which are shown in Figures 7 and 8. Five neural networks considered are MLP 8-11-4, MLP 8-5-4, MLP 8-8-4, MLP 8-4-4, and MLP 8-5-4, which are different in the number of nodes of each layer, the hidden activation function, and the output activation function. From Figures 6 and 7, it is clear that boosted tree algorithm outperforms other algorithms on both the gain–percentile and the response–percentile charts, which means this algorithm performs better when identifying the fault of head sheave swing. Prediction accuracy also illustrates that boosted tree has the best performance in solving this particular problem. Different prediction accuracy is listed in Table 4, which proves the same conclusion, so the algorithm of boosted tree is finally employed. 

The concept of boosted tree algorithm is a novel way to combine the prediction or classification of some basic decision trees. In this algorithm, the basic decision trees classify the data independently, and then, each classifier is assigned a weight which is inversely proportional to its different accuracy. That is, for those classifiers which have a higher misclassification rate, a greater weight will be given and those with a lower misclassification rate will be assigned a lesser weight. When applied on the learning data, the boosted tree algorithm generates a sequence of classifiers and then combines them based on their different weights to form a single best classification.

**Results and discussion**

To verify the comparison result, the methods above are applied on a data set which includes features extracted from vibration signals collected under different fault patterns of head sheaves. During the training process of boosted trees, shown in Figure 9, as the number of trees increases, for the training data, the average multinomial deviance goes down continuously and approaches around zero at number 200. However, for the test data, after a period of decline, the average multinomial deviance does not fall substantively any more. The optimal number of trees is 112 according to the trend and the maximum tree size is 3. Models of other algorithms, including neural network, K-nearest neighbor, Naive Bayes classification, and support vector, are trained with the same data set. A small data set of 20 samples are finally used to test all the obtained models. Among them, same as the analysis, the boosted tree algorithm predicts all 20 cases correctly, which means a prediction accuracy of 100% as shown in Figure 10. For other algorithms, the neural network predicts 14 cases correctly, and the number of correctly identified cases by K-nearest neighbor, Naive Bayes classification, and support vector are 12, 4, and 3, respectively. The result shows that among the algorithms mentioned above, prediction by the boosted tree method has the maximum accuracy.

**Conclusion**

With FTA, faults of head sheaves are analyzed, which shows headframe inclination, bearing faults, and excessive swing of head sheaves are the three most serious
failure patterns. A test rig is set up to simulate the faults and collect vibration signals under different fault patterns. Features are extracted from vibration signals and screened according to their significance. Five among eight initially extracted features are remained, that is, RMSE, Min, VPP, Std, and Skewness. Several data mining algorithms are compared based on the sample set collected from experiments on the test rig, and the result shows that the boosted tree algorithm outperforms other methods in the fault diagnosis of head sheaves.

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