Electrostatic monitoring of rolling bearing with multi-sensor fusion under variable operating conditions

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Abstract. The friction and wear condition of rolling bearing can be detected and monitored by the novel electrostatic sensing technique. It has been verified under stable operating conditions, while the change of conditions impact a lot for the electrostatic original signals. This paper introduced a new method called moving window local outlier factor (MWLOF) to process electrostatic monitoring signals of rolling bearing under variable operating conditions. Compared with traditional features, the extracted features can reduce the impact and accurately reflect the wear condition of the bearings in the load and accelerated life tests. It can detect early faults earlier and has a better sensitivity and performance degradation trend than conventional techniques, which leads to a better industrial application in future.

1. Introduction
At present, an electrostatic induction-based monitoring technology featuring high sensitivity has provided a new method for condition monitoring of tribological contacts. Early investigations in electrostatic monitoring were focused predominantly on sliding wear using a Pin on Disc and a PLINT reciprocating test rig [1-5]. Then the technique has also been applied to the monitoring of rolling contacts, including steel rolling element bearings on a bearing test machine [6-10] and of slide-rolling contacts using a twin-roller machine [11]. Two types of electrostatic sensors, i.e. wear-site sensor (WSS) and oil-line sensor (OLS), were invented and mounted on the machines [12-15].

The electrostatic monitoring system comprises a passive sensor connected to a signal conditioner (a charge amplifier) from which a voltage signal may be recorded and processed. When an isolated charged particle passes the electrostatic sensor face, electric field lines due to charge \( Q \) terminate on the sensor face. The electrons on the sensor redistribute to balance the additional charge in the vicinity of the sensor resulting in a current flow, which is measured by the conditioner. The signal conditioning thus converts the detected charge into a proportional voltage signal.

Although some creative investigations [1-15] have been undertaken on the electrostatic monitoring techniques through experimental studies, limited efforts have been made to investigate the influence of variable operating conditions on characteristic detection. Information fusion with multi-sensors is an intelligent method to solve the problem in industry [16-18]. This paper proposed a new method called moving window local outlier factor considering the change of operating condition for electrostatic monitoring. Experiments have been conducted with rolling bearings using electrostatic WSS under variable operating conditions to verify the theory and contribute to future application.
2. Information fusion algorithm of multi-electrostatic signal

A new method called moving window local outlier factor (MWLOF) has been developed to solve the influence of working condition changes in the process of industrial control [16-18]. The mobile window strategy is introduced, and a model updating mechanism based on local outliers of mobile windows is proposed, which is compared with other adaptive local outliers fault detection algorithms. The results show that this method can flexibly use the local structure information of raw data, and is not affected by complex data distribution. It can quickly update and reduce operation amount when switching conditions, and effectively improves the efficiency of real-time monitoring. Therefore, based on this algorithm, combined with effective feature extraction of electrostatic sensor, the electrostatic signal is fused to achieve multi-site and time-varying multi-sensor information monitoring.

2.1. Traditional electrostatic features

Considering the large amount of data, caused by a high sampling frequency and long time duration, the original signal is hard to intuitively and effectively reflect the change trend of electrostatics level. Thus, Feature extraction is introduced to signal processing of electrostatic monitoring. Various methods of feature extraction were investigated for performance degradation assessment, diagnosis and prognosis in mechanical systems, especially in the field of vibration [15]. The traditional extracted features of signal in the time domain, such as root mean square, peak-peak parameter (P-P), kurtosis and skewness, are listed in Table 1. The presence of abnormal change, which is always related to faults, can be detected by these features timely.

| Feature          | Equation                                                                 |
|------------------|---------------------------------------------------------------------------|
| Mean value $x_m$ | $x_m = \frac{\sum_{n=1}^{N} x(n)}{N}$                                 |
| Root mean square $x_{rms}$ | $x_{rms} = \sqrt{\frac{\sum_{n=1}^{N} (x(n))^2}{N}}$                   |
| Standard deviation $x_{std}$ | $x_{std} = \sqrt{\frac{\sum_{n=1}^{N} (x(n)-x_m)^2}{N-1}}$              |
| Peak-Peak $x_{pp}$ | $x_{pp} = \max(x(n)) - \min(x(n))$                                     |
| Skewness $x_{sk}$ | $x_{sk} = \frac{\sum_{n=1}^{N} (x(n)-x_m)^3}{(N-1)x_{std}^3}$          |
| Kurtosis $x_{kur}$ | $x_{kur} = \frac{\sum_{n=1}^{N} (x(n)-x_m)^4}{(N-1)x_{std}^4}$         |

Where $x(n)$ is a signal series for $n=1, 2, \ldots, N$, $N$ is the number of data points.

2.2. Time-varying electrostatic monitoring process in multiple operating conditions

After the electrostatic features extraction, the process of information fusion with MWLOF algorithm considering the change of operating condition is shown in Figure 1. The value of lof is the output parameter for electrostatic monitoring after information fusion. The core of the algorithm is the same and detailed presented in paper [16-18]. In this algorithm, it is necessary to select and determine the appropriate size of the window and the number of adjacent points by weighing the calculation efficiency and the model accuracy. If the selected window is small, it can improve the computational efficiency of the algorithm, but it will reduce the accuracy of the fault detection model. If the selected window is large, it will improve the accuracy of the fault detection model, but it will also reduce the computational efficiency of the algorithm. Similarly, if the number of neighbor points selected is small, it can speed up the operation efficiency of the algorithm, but it is not conducive to the accurate expression of the local density of the sample points, while the large number of adjacent points will
cause the difference between the lof value of the normal sample and outliers. According to the test results of investigates [16-18] and simulation show that the [700, 800] is a suitable range of L window, the number of neighbor points k=30 is more suitable in value; therefore the following electrostatic monitoring process of experimental data analysis, chooses the L=700 as the actual size of the window, and select the nearest neighbor point number k=30. At the same time the algorithm control limits were set at 99% confidence level.

3. Experimental result analysis
The variable condition life cycle test of the rolling bearing is conducted on the ABLT-1A provided by Hangzhou Bearing Test and Research Centre (HBRC). The test rig has been implemented by Zhang [10]. Structure of the electrostatic sensors, installation position and data acquisition system are also introduced with detailed description. The only difference for the experiments is the changing of variable operating conditions.

In the experiment, the initial working condition is 20 kN of radial load and 2000 r/min of speed. After running 800 samples, the radial load is increased to 30 kN, and the speed is increased to 3000 r/min. A total of 2290 monitoring samples are monitored in a time series by running to the final bearing failure under the new switching condition. The results of the integrated electrostatic monitoring experiment are shown in figures 2 to figure 6. Figure 2 shows the results of the MWLOF algorithm by considering the change of working condition. Figure 3 shows the results using MWLOF algorithm without considering the change of working condition. Figure 4 is the result of the LOF

![Figure 1. Process of electrostatic information fusion.](image-url)
algorithm without moving window strategy. Figure 5 is part of the WSSs fusion before extraction (Wear-site sensors) monitoring results of parameters of the single static features. Figure 6 is the experimental bearing the final failure figure.

![Figure 2. MWLOF algorithm with considering the change of operating condition of experiment one.](image1)

![Figure 3. MWLOF algorithm without considering the change of operating condition of experiment one.](image2)

![Figure 4. LOF algorithm of experiment one.](image3)

![Figure 5. Traditional electrostatic features of experiment one.](image4)

![Figure 6. Failure of inner ring of experimental bearing.](image5)

Figure 2(a) is the threshold value of the lof value and the control limit calculated at the corresponding time in the whole life cycle of the rolling bearings in the whole life cycle. Figure 2(b)-(e) is the change trend of the sample and threshold after the corresponding interval amplification in this result. As can be seen from figure 1 rolling bearing electrostatic lof signal in the whole life cycle, the occurrence of early fault before the first 1900 samples remained stable, compared with after the failure of static lof is smaller, and less than the corresponding time threshold, that rolling bearing remained in normal working state. After 800th samples of the change of the working condition, the static lof value appeared obviously higher pulse, and went down to the normal level after a period of time. The MWLOF algorithm considering the switching of working conditions will also be regarded as normal after the 800 samples, and the higher lof value caused by the change of working condition is
also normal, and the corresponding new threshold is continuously given, so that the lof value of the switch is not judged to be abnormal until it reaches the normal level. Therefore, the rolling bearing has no exception in the life cycle of the early fault (the sample point before the 1911st samples in this experiment). Bearing run to 1911st samples after began to frequent and abnormal value exceeds the threshold, the bearing performance degradation in early state, may produce early fault weak pitting adhesive; began to run to 2099th samples after multiple outliers are continuous, that the bearing has entered the wear is serious, the performance is further degraded, there may be some serious fault cracks and flaking; running to 2156th samples after static lof value is always greater than the threshold and rising until the system is far greater than the threshold, indicating that the bearing has entered a serious performance degradation state, bearing wear serious near complete failure. At this time the shutdown was checked and it was found that serious wear and tear in the inner ring of the experimental bearing had failed, as shown in Figure 6. The experimental process, from the early to the stable operation of bearing early degradation and eventual failure, electrostatic comprehensive monitoring lof value and the change trend of the monitoring results and the actual variation of rolling bearing wear state is consistent, at the same time with the experimental machine own vibration and temperature monitoring results are basically the same, and the lof value of electrostatic bearings the state reflected in the beginning to end down there obviously degraded performance from weak fault early, that consider MWLOF electrostatic monitoring signal switching fusion algorithm can be used for degradation state characterization of the whole life cycle of rolling bearing is adopted, comprehensive monitoring of the fusion algorithm is applied to the electrostatic sensor.

A comparison between figure 2 and figure 3 it can be seen that the MWLOF algorithm does not consider the electrostatic monitoring conditions result in bearing performance degradation in early state, namely 1911st samples after the frequent and abnormal value exceeds the threshold, to a sample of 2099th began to appear after multiple outliers are continuous, then static lof value 2156th after the sample is always greater than the threshold and rising until the system is far greater than the threshold, the comprehensive monitoring results of static MWLOF algorithm until the final failure stop this phase of the monitoring results and considering the conditions are basically the same. But the corresponding static lof in a sample of 800th and the subsequent period of time or when conditions change the value exceeded the control limit threshold, so will the change because of changes in the electrostatic signal conditions misdiagnosed as abnormal state of rolling bearing; at the same time, in 1200th to 1800th of the sample in the sample period, because no the new sample conditions lead to changes in the update in the model, so will a lot of normal samples under the new condition of stable operation is judged as abnormal. And the same time the two stages in the corresponding experiment machine own vibration and temperature monitoring are not any abnormal degradation at experimental bearing normal operation and no early fault or performance, so the algorithm of monitoring after switching results in error, which belongs to the false alarm. It is proved that the MWLOF algorithm considering the change of the working condition is better than the MWLOF algorithm that does not consider the change of the working condition in the static comprehensive monitoring of the rolling bearing.

By comparing figures 2, 3 and 4, we can see that the monitoring results of LOF algorithm without mobile window strategy are similar to those of MWLOF algorithm without considering the condition switching. From a sample of 1911st after frequent abnormal value exceeds the threshold; consecutive multiple outliers and is always greater than the threshold value of the sample point (respectively 2094th and 2143rd samples) and MWLOF algorithm of monitoring sample time interval is similar; the occurrence condition of switching and stable operation in the new condition (800th samples after) were monitored for many actual false alarm of abnormal value. Further, compared with MWLOF algorithm, because its threshold does not always update with acquisition samples, it always has a certain value. Therefore, under the initial working conditions, there are many actual false alarm values in the stable running interval (first to 800 sample points). The results showed that considering the condition changes of MWLOF, without considering the condition change of MWLOF and not the moving window strategy LOF three algorithm to monitor the abnormal value in the whole life of the
bearing in total were used in this experiment: 257, 332 and 426, when the two visible monitoring algorithm used after there will be a large number of false alarms, which is not conducive to the effective electrostatic monitoring. In fact, not control LOF algorithm using moving window strategy of the threshold and the training data is directly related to the training data generated when the threshold is low, will lead to the emergence of a large number of false alarm, and when the threshold is higher to generate training data, the corresponding early performance degradation when the lof value is below the threshold, which will reduce the detection the ability of the system to the early fault, so this method is not suitable for electrostatic comprehensive monitoring.

As shown in figure 5(a) to (d) monitoring results of rolling bearings were part of a single feature extraction experiment in a single static sensor output signal of the whole life cycle, namely fusion before the static parameters in the same corresponding sample values, respectively, the root mean square value, margin index the peak to peak value and pulse index. We can see that the dimensionless parameters which have the RMS value and the peak value of the degradation trend has good performance, and also exists in a continuous pulse condition change corresponding parameters; and the dimensionless margin index and pulse index also exist certain trends but not obvious, and the changes of working conditions on the two parameters of the signal no effect; physical meaning and characteristics of the monitoring results and the corresponding parameter match, also proves the reliability of the electrostatic sensor during the experiment in monitoring the output signal. If the online monitoring of rolling bearing by using only a single static characteristic parameters of these fusion before, will have the following problems, the RMS value of the degradation trend of good performance and a peak value, because it is a dimensionless parameter, each monitoring system and the influence of different environment, the average level of the total amount of the electrostatic the difference can not be stable at a certain magnitude or a specific range of values, so it is difficult to give a general threshold or threshold with the sample update to the judgment of the bearings running state, and these parameters will be subject to conditions resulting in false alarm generation; for less affected by the change of working condition dimensionless parameter margin index and pulse index, the monitoring value of performance in the whole life cycle of the degradation trend is not obvious and there are more random pulse Therefore, it is difficult to give a better threshold for online monitoring and state evaluation. Therefore, it is difficult to achieve effective electrostatic monitoring only by relying on single feature parameters extracted before fusion.

To sum up, the MWLOF algorithm considering the change of working conditions has better electrostatic monitoring ability than the MWLOF algorithm without considering the change of working conditions, the LOF algorithm without mobile window strategy and the single characteristic parameter without fusion. The algorithm can be effectively applied to the monitoring of the information fusion of the multi-sensor static multi-sensor. In order to further verify the validity and repeatability of the algorithm and experiment, more experiments are carried out after the replacement of the bearing and have the same results. Meanwhile, the time consumption in the fusion process is very fast within 10 sampling points to suit the real time monitoring.

4. Conclusions
Information fusion with multi-sensors is an intelligent method for condition monitoring and evolution in industry. This paper proposed a new fusion method called MWLOF for early fault monitoring, which is applicable to the electrostatic monitoring of rolling bearings. The MWLOF method considering the change of operating conditions proposed in this paper is better than the algorithm without considering the change of operating conditions. Also it is better than the LOF algorithm and traditional parameters. It can detect the occurrence of early faults at an earlier time, so as to provide sufficient time for maintenance decision making. The method proposed in this paper cannot be affected by the change of operating conditions and thus can be more applied to the actual industry production.
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