Fusion of the Dimensionless Parameters and Filtering Methods in Rotating Machinery Fault Diagnosis

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***Abstract*—For the problem of large dimensionless index fluctuations in rotating machinery complex fault and that the corresponding scope is difficult to determine. In this paper proposes a rotating machinery complex fault method that combined dimensionless and the least squares method filtering. This method implementation filtering and determine the scope of the dimensionless index. By doing experiments with 8 kinds of bearing failure data of petrochemical rotary sets, comparing four filtering methods, the scope of the dimensionless index was established, and the text combined dimensionless index respectively with Kalman (EKF), the weighted average, moving average, the least squares method filtering.**

***Index Terms*—Dimensionless Parameters; Kalman Filter; Combination Faults; Fault Diagnosis; Moving Average Filter; Weight Filter**

I. INTRODUCTION

That large engineering system complexity continues to increase requires higher safety and reliability of the system. Through the analyzing system health status, fault diagnosis technology determine the type of failure, for the timely and effective maintenance and health systems management provides a scientific basis, so that in the field of aviation, aerospace and other need higher security requirement, has a good application prospect [1, 2]. Particularly, rotating machinery and equipment (such as rotation bearings, turbines, compressors, fans, etc.) is the key equipment in petroleum, chemical, metallurgy, machinery manufacturing, aerospace, and other important engineering filed. Therefore, the study of such equipment fault diagnosis method has been a hot topic in this field.

In rotating machinery fault diagnosis usually use the time domain or frequency domain analysis of vibration monitoring data for fault diagnosis [2-5]. Rotating machinery in the event of a failure, however, vibration monitoring signals tend to have a large number of non-linear, random, non-ergodic information, and bring great difficulty in fault signal analysis [6]. Considering the time-domain signal of vibration is the most basic and original signal, if failure characteristics can be extracted directly from the time-domain signal, and analyze fault diagnosis, so that maintain the basic characteristics of the signal will be very beneficial [1-2]. In the time domain analysis, the probability density function of vibration signals can better reflect the fault information. Through the probability density function of the vibration signal, it has been derived dimensional index (such as the mean and RMS values, etc.) and dimensionless index (such as waveform, margin index, pulse, etc.) in the amplitude domain [1-2, 6-7]. In practice, although a dimensional index is sensitive to the fault characteristics, its value will increase with the development of the fault, but also because working conditions (such as load, speed, etc.) changes, it is easily affected by interference, performance is not stable enough [1]. By contrast, the dimensionless index is not sensitive to the disturbance of vibration monitoring signal, performance is stable. In particular, these dimensionless index are not sensitive to the change of amplitude and frequency of the signal, namely, it has little relationship with working conditions of the machine [1-3, 5-7]. Therefore, the dimensionless index has been widely used in fault diagnosis of rotating machinery. In dimensionless index, pulse index and kurtosis index is more sensitive to impact type fault, especially in the early failure, the large amplitude of the pulse is less, other parameter values increase is not much, but kurtosis index and pulse index rise faster, so that failure of the range is larger. It is difficult to determine the scope of the composite fault interval [1-3, 5-7].

In order to reduce the error, determine the scope of the dimensionless index, and narrow the scope of the machinery recombination fault interval, first excluding outliers of the dimensionless index, and then filtering. There are many ways to achieve signal filtering, Kalman filtering is usually used in aviation and aerospace aspects, for example, against the data collected by marine dynamic positioning multiple sensors in real-time fluctuation, causing controller move frequently, resulting in boat actuators adjust frequently, and increasing its mechanical wear, Jianbin Xiong proposes a method to collect data online by DPS multi-sensor and filtering based on OPC technology, achieving ship signal filtering indoor, but the method is easy to diverge [9]. In order to solve the problem of Kalman filtering divergence, Wang Qinruo proposed a blend adaptive Kalman filter

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algorithm [10], the calculating of the method is complex and it is difficult to effectively exclude outliers. Ref. [11] proposes a method to resist outliers based on adaptive moving average fitting. This method achieves outlier removal effectively, and filtering, but this method is only suitable for signal fluctuates up and down in the vicinity of a certain scale. At present, the dimensionless index combined with filtering method to achieve narrow the scope of the rotating machinery fault interval, has not yet been reported. In this paper, adopting dimensionless index combined with the method of least squares filtering respectively, achieve the signal filtering processing, and narrow the scope of the rotating machinery fault interval.

II. DESCRIBES THE PROBLEM

Definitions 2.1 [1-2, 5] Dimensionless index is made up of the ratio of two amount with the same dimension. When describing a particular system, it has certain physical meaning, fault diagnosis for dimensionless parameter index:

$$\Delta\eta_x = \frac{[\int_{-\infty}^{+\infty} |x|^{\mathrm{T}}\ \xi(x)dx]^{\frac{1}{\mathrm{T}}}}{[\int_{-\infty}^{+\infty} |x|^{m}\ \xi(x)dx]^{\frac{1}{m}}} \tag{1}$$

x is vibration amplitude, $\xi(x)$ is probability density function of vibration amplitude. Multiple historical monitoring data of single fault can be calculated.

Considering rotating machinery in the event of a failure, vibration monitoring signals tend to have a large number of non-linear, random, non-ergodic information, lead to great difficulty in fault signal analysis. Although a dimensional index is sensitive to the fault characteristics, its value will increase with the development of the fault, but also because working conditions (such as load, speed, etc.) changes, it is easily affected by interference, performance is not stable enough. The dimensionless index is not sensitive to the disturbance of vibration monitoring signal, performance is stable. In dimensionless index, pulse index and kurtosis index is more sensitive to impact type fault, especially in the early failure, the large amplitude of the pulse is less, other parameter values increase is not much, but kurtosis index and pulse index rise faster and fluctuate larger, therefore, these two indexes are more sensitive to early failure of rotating machinery, resulting in fault interval range increases, and it is difficult to distinguish. Using four kinds of filters are filtering to narrow the scope of the fault interval.

Question: For rotating machinery fault signal of dimensionless index, how to narrow the scope of the fault and determine the scope of the dimensionless indexes corresponding fault interval.

III. DIMENSIONLESS INDEX CALCULATION AND FAULT INTERVAL DETERMINATION

A. Dimensionless Index Calculation

In engineering applications, dimensional index is sensitive to the fault characteristics, its value will increase with the development of the fault, because working conditions (such as load, speed, etc.) changes at the same time, it is easily affected by interference, performance is not stable enough [2]. By contrast, the dimensionless index is not sensitive to the disturbance of vibration monitoring signal, performance is stable. In particular, when the change of machine working conditions is large these dimensionless indexes are not sensitive to the change of amplitude and frequency of the signal.

Hypothesis 3.1 [1-2, 5] Under the Definition 2.1 and $T = 2, m = 1$, then the waveform index:

$$S_f = \frac{[\int_{-\infty}^{+\infty} |x|^2\ \xi(x)dx]^{\frac{1}{2}}}{[\int_{-\infty}^{+\infty} |x|\xi(x)dx]} = \frac{\sqrt{E(|x|^2)}}{E(|x|)} \tag{2}$$

Similarly, (1) Where $T = \infty, m = 1$, pulse index I_f is available :

$$I_f = \lim_{T\to\infty} \frac{[\int_{-\infty}^{+\infty} |x|^T\ \xi(x)dx]^{\frac{1}{T}}}{[\int_{-\infty}^{+\infty} |x|\xi(x)dx]} = \frac{\lim_{T\to\infty} \sqrt[T]{E(|x|^T)}}{E(|x|)} \tag{3}$$

where $T = \infty, m = 1/2$, margin index CL_f is available :

$$CL_f = \lim_{T\to\infty} \frac{[\int_{-\infty}^{+\infty} |x|^T\ \xi(x)dx]^{\frac{1}{T}}}{[\int_{-\infty}^{+\infty} |x|^{1/2}\ \xi(x)dx]^2} = \frac{\lim_{T\to\infty} \sqrt[T]{E(|x|^T)}}{[E(\sqrt{|x|})]^2} \tag{4}$$

where $T = \infty, m = 2$, margin index C_f is available :

$$C_f = \lim_{T\to\infty} \frac{[\int_{-\infty}^{+\infty} |x|^T\ \xi(x)dx]^{\frac{1}{T}}}{[\int_{-\infty}^{+\infty} |x|^2\ \xi(x)dx]^{1/2}} = \frac{\lim_{T\to\infty} \sqrt[T]{E(|x|^T)}}{\sqrt{E(|x|^2)}} \tag{5}$$

Dimensionless index is made up of the ratio of two amounts with the same dimension. In this paper, monitor signal based on the probability density function of the monitoring signal, namely dimensionless index is a ratio, which don't affected by signal absolute level, and the relationship between the sensitivity of vibration detector, amplifier and the magnification is not large, so the monitoring system without calibration bring convenience in the actual equipment fault diagnosis [5].

Lemma 3.1 [1, 5-6] Dimensionless index between the mathematical operations such as addition, subtraction, multiplication, and division, the index is still dimensionless.

B. Fault Interval Determination

The dimensionless index in the study of fault diagnosis: First test by petrochemical core units, collect data online real-time, calculate normal state of the rotation unit and all kinds of dimensionless index parameter when occur each failure. Then, calculate maximum value and minimum value of each dimensionless index as the scope of core units in normal state or all kinds of fault states.

Hypothesis 3.2 Collect N monitoring data under the single fault of vibration data ε, N is relatively larger.

Conclusion1 Under the condition of Definitions 2.1, Hypothesis 3.1 and Hypothesis3.2, expectations of the dimensionless index approximate:

$$\overline{\varepsilon^{T}} = E(|\varepsilon|^{T}) = \frac{1}{N}\sum_{i=1}^{N}|\varepsilon_i|^{T} \tag{6}$$

So, dimensionless index $\Delta\eta_x$ approximate:

$$\Delta\eta_x = \sqrt[T]{\overline{\varepsilon^{T}}} \Big/ \sqrt[m]{\overline{\varepsilon^{m}}} \tag{7}$$

where $T=\infty$, $\sqrt[T]{\overline{\varepsilon^{T}}} \approx \max_{j=1,2,\cdots N}|\varepsilon_j|$.

Conclusion 2 Under the condition of Definitions 2.1, Hypothesis 3.1 and Hypothesis 3.2, sets of Vibration monitoring data of a single fault history $\varepsilon_1,\varepsilon_2,\cdots,\varepsilon_{N_k}$, value range $\overline{\varepsilon^{T}} \in [\alpha_T,\beta_T]$ of $\overline{\varepsilon^{T}}$ can be calculated, then the dimensionless index fault interval is:

$$\begin{aligned}\Delta\eta_x &= \frac{[\int_{-\infty}^{+\infty}|x|^{T}\,\xi(x)dx]^{\frac{1}{T}}}{[\int_{-\infty}^{+\infty}|x|^{m}\,\xi(x)dx]^{\frac{1}{m}}} = \frac{\sqrt[T]{\overline{\varepsilon^{T}}}}{\sqrt[m]{\overline{\varepsilon^{m}}}} \in [c_\varepsilon, d_\varepsilon] \\ &= \frac{[\sqrt[T]{\alpha_T},\sqrt[T]{\beta_T}]}{[\sqrt[m]{\alpha_m},\sqrt[m]{\beta_m}]} \in [\frac{\sqrt[T]{\alpha_T}}{\sqrt[m]{\beta_m}},\frac{\sqrt[T]{\beta_T}}{\sqrt[m]{\alpha_m}}]\end{aligned} \tag{8}$$

IV. Combinations of Filter and Dimensionless Index

For calculating real-time data dimensionless index of rotating machinery, data fluctuation is larger, this paper filtering by the dimensionless index combined with least square filter respectively.

When using the method of least squares filter (Least Square Method filter, LSM), how to obtain the nonlinear parameter estimates, Ref. [14] proposed a Least square method filter based on random function, the formula is:

$$s[n] = A\varphi[n;\theta] \quad n = 0,1,\cdots \text{N-1} \tag{9}$$

$$s[n] = A\exp(j2\chi f_0 n) \tag{10}$$

$$J(A,f_0) = \sum_{n=0}^{N-1}|x[n] - A\exp(j2\chi f_0 n)|^2 \tag{11}$$

where $x[n]$ represent observation data, n represent the number of filtering data, $s[n]$ represent filtering value. The method using a computer is easy to implement, but to calculate the inverse of matrix, it is difficult to determine the solution of the irrational root, and it can't join in constraints of time domain and frequency domain.

V. Examples of Complex Rotating Machinery Fault

Currently fault simulation platform in petrochemical rotating units laboratory have multiple equipment parts, mainly are the fault shaft (eccentric shaft, split shaft, curved shaft, no-symmetry shaft, bearing crack outsider, bearing crack insider, etc.) as well as normal shaft. In this paper we collect the data with the method of Ref. [1-2, 5], namely collect vibration acceleration signal of measurement unit online by EMT490. In order to produce a composite failure, when obtain the data, it need to take into account the different loads, different speeds, different frequencies [15], etc., we obtain five kinds of speed, light load and the lack of bearing, bearing wear, eccentric shaft, split shaft, curved shaft, no-symmetry shaft and normal shaft under overloaded three kinds of radial load, nine state in total. In the experiment, a group according to the 1024 sampling points, each of the indexes 20 from each group, of which the first set of each type of data used to train the state 10, the 10 sets of data for verification [1], according to the indicators 10 maximum and minimum range of the group as the indexes. Calculate index range in each state of different shaft fault state, it is shown in Table 1. As can be seen from Table 1 after obtaining the real-time monitoring signals, using the Eq. (2) - (5), to calculate the scope of waveform index, peak index, pulse index, margin index and kurtosis index are duplicate (namely, called composite fault), and the scope of the interval is large, it is difficult to distinguish dimensionless index interval between normal equipment and faulted equipment strictly [16, 17]. In order to solve the above problem, this paper uses the four kinds of filter method of the part four, filter dimensionless index have been calculated, filter out some interference signals, to reduce the fault interval. The concrete implementation process is shown in Figure 1.

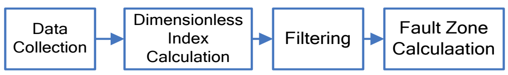

Figure 1. Determining the fault zone of flow

Dimensionless indexes combined with four kinds of filter, can filter out interference information effectively, to reduce the fault interval, and provide the effective basis for future fault diagnosis. In this paper, waveform index, peak index, pulse index, margin index and kurtosis index in the state of eccentric shaft, split shaft, curved shaft, no-symmetry shaft [16-17], crack shaft and normal shaft, eight state, totally use four kinds of filter of the paper, the result is shown in Figure 2 ~ 9, fault scope is shown in Table 2 ~ 9 after filtering.

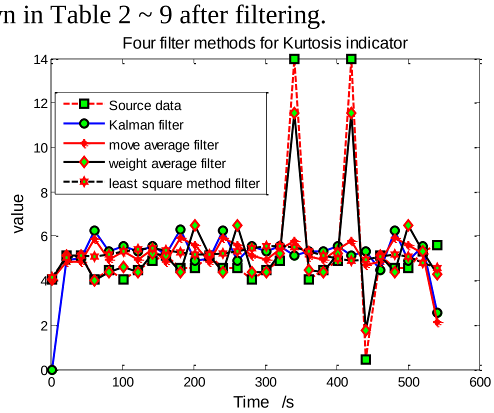

Figure 2. Four filter methods for bearing wear

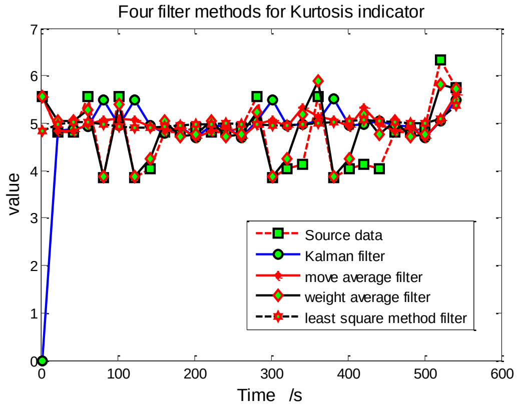

Figure 3. Four filter methods for bearing crack in outsider

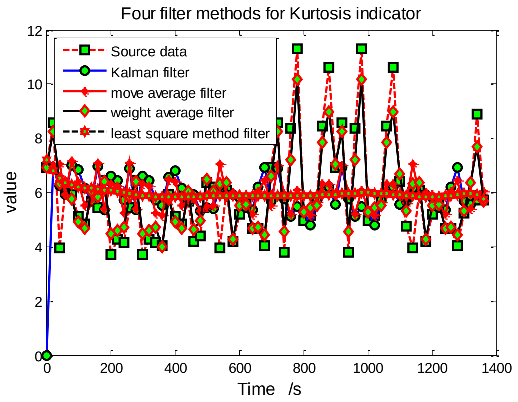

Figure 4. Four filter methods for bearing crack insider

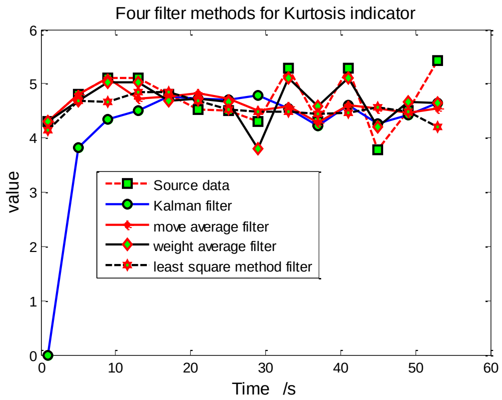

Figure 5. Four filter methods for curved shaft

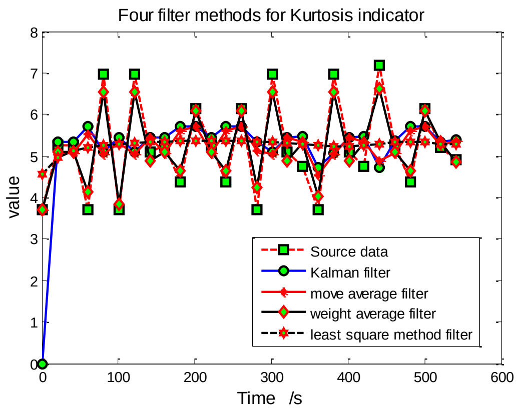

Figure 6. Four filter methods for Lack of bearings

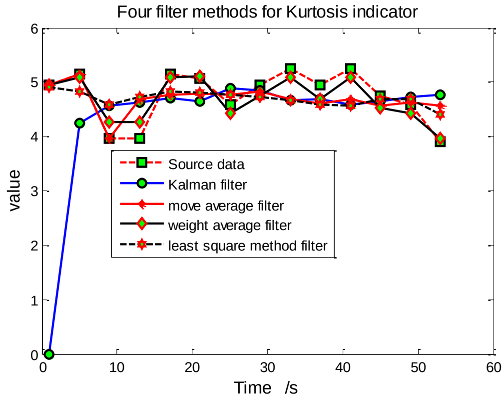

Figure 7. Four filter methods for eccentric shaft

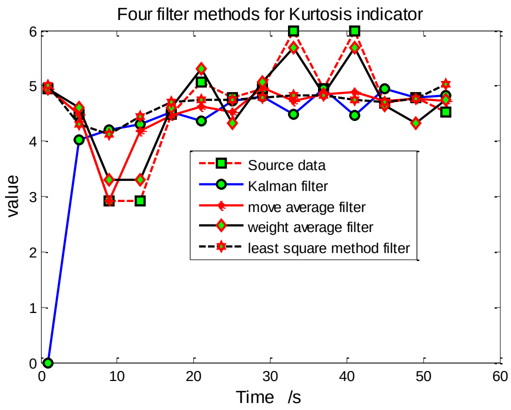

Figure 8. Four filter methods for cracked shaft

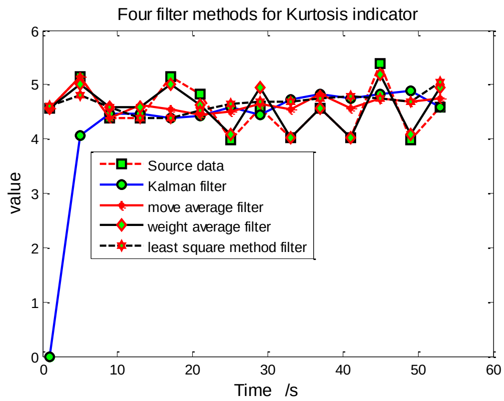

Figure 9. Four filter methods for no-symmetry shaft

As shown in Table 2 ~ 9 and Figure 2 ~ 9, the four filtering method can narrow down the interval effectively, and we can select different methods according to the different environment and different need. Where estimating stochastic dynamic system state, Kalman filtering may be used, this method is based on state space model of the system, using a moment before the state estimated value and current observed value to get the state estimated value for the next moment, achieving recursive, this method is suitable for computer implementation. The method of dimensionless index combine with moving average filter is suitable for a certain value scope of fluctuating up and down, and is not suitable for the online data filter which occur outliers frequently. Dimensionless index and the weighted average filter are suitable for online data which have large lag time and the system whose sampling period is short, but is not suitable for online data filtering of high-speed rotation petrochemical machinery and equipment. Dimensionless indicators and least squares filter need to calculate the inverse matrix, and will not be

TABLE I. BEARING NORMAL AND FAULT STATE DIMENSIONLESS INDEX INTERVALS (ACCELERATION)

Unit Working State	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Normal Shaft	1.2091~1.2870	2.2240~3.9359	2.7514~4.9907	3.2226~6.0526	2.4246~3.6479
Bearing Wear	1.0612~1.5949	0.2303~8.7538	0.2513~13.9611	0.2684~17.7876	2.9013~26.3391
Bearing Crack Outsider	1.2375~1.4265	2.6251~6.1170	3.4025~8.6839	4.1249~10.8383	2.6901~7.6141
Bearing Crack Insider	1.2328~1.6799	2.8012~8.9731	3.5636 ~13.415	4.2459~16.7635	2.6026~20.7573
Curved Shaft	1.2302~1.3255	1.8863~4.1650	2.3206~5.4257	2.6831~6.5626	3.3283~4.0515
Lack Of Bearing	1.2356~1.4946	2.5096~6.1057	3.1301~8.6021	3.7089~10.7216	2.7353~8.3781
Eccentric Shaft	1.2644~1.3277	3.0769~3.9559	3.9109~5.2521	4.6441~6.4544	3.2241~4.1031
Crack Shaft	1.2467~1.3174	2.3342~4.5670	2.9101~5.9884	3.4182~7.3012	3.5065~4.0086
No-Symmetry Shaft	1.2829~1.3349	3.1001~4.5470	3.9771~6.0672	4.7788~7.4463	3.3366~4.6789

TABLE II. THE SCOPE OF BEARING WEAR AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.0612~1.5949	0.2303~8.7538	0.2513~13.9611	0.2684~17.7876	2.9013~26.3391
KF	0.6410~1.3796	1.6496~4.6495	2.0748~6.6026	2.4539~8.2177	1.5689~8.6002
MAF	1.1334~1.3605	1.3836~4.4479	1.6126~6.1025	1.7932~7.4894	3.5103~6.8815
WA	1.0807~1.5338	0.4281~7.3577	0.4664~11.5408	0.4962~14.6645	3.0342~20.9111
LSM	1.2557~1.3328	3.2900~4.1506	4.1553~5.5643	4.9332~6.7976	3.3364~5.1636

TABLE III. THE SCOPE OF BEARING CRACK OUTSIDER AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2375~1.4265	2.6251~6.1170	3.4025~8.6839	4.1249~10.8383	2.6901~7.6141
KF	0.6506~1.3394	2.2169~4.3489	2.8300~5.8145	3.3403~7.1182	2.0010~4.8505
MAF	1.2725~1.3401	3.5411~4.2676	4.5690~5.6627	5.4800~6.9296	3.3762~4.7260
WA	1.2533~1.3978	2.8991~5.3951	3.7772~7.5433	4.5600~9.4629	2.9543~6.6626
LSM	1.2799~ 1.3322	3.7777~ 4.1755	4.8448~5.5853	5.7983~6.8283	3.5068~4.5346

TABLE IV. THE SCOPE OF BEARING CRACK INSIDER AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2328~1.6799	2.8012~8.9731	3.5636~13.4152	4.2459~16.7635	2.6026~20.7573
KF	0.7414~1.4531	2.4272~5.3061	3.5313~7.6609	4.5618 ~9.7871	3.1278~8.6235
MAF	1.3030~1.4495	3.5802~5.2485	4.7326~7.4414	5.7788~9.5213	3.5833~8.0354
WA	1.2586~1.6244	3.0713~7.8838	3.8850~11.7275	4.6134~14.7297	3.0183~16.7261
LSM	1.3393~ 1.4017	4.1609 ~ 5.0759	5.6108~7.2045	6.9564~ 9.0511	4.8099~7.3497

TABLE V. THE SCOPE OF CURVED SHAFT AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2302~1.3255	1.8863~4.1650	2.3206~5.4257	2.6831~6.5626	3.3283~4.0515
KF	0.6632 ~1.3015	1.6836~3.7118	2.1908~4.8347	2.6427 ~5.8484	1.8643~3.7696
MA	1.2851~1.3029	3.2849~3.7132	4.2410~4.8286	5.0978~5.8323	3.6433~3.7731
WAF	1.2469~1.3160	2.2887~3.9122	2.8739~5.0998	3.3847~6.2203	3.5058~3.9892
LSM	1.2831~ 1.3088	3.1769 ~ 3.7449	4.1344~ 4.8804	4.9907~5.9021	3.6250~3.7416
LSM	1.2944~ 1.3516	3.4889 ~ 4.0123	4.5605~ 5.3627	5.5346~6.6324	3.7601~4.7038

TABLE VI. THE SCOPE OF LACK OF BEARING AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2356~1.4946	2.5096 ~6.1057	3.1301~8.6021	3.7089~10.7216	2.7353~8.3781
KF	0.6540 ~1.3676	1.4764~4.3533	1.8947~5.8497	2.2864 ~7.2190	1.6557~5.2505
MAF	1.2885~1.3646	3.2569~4.4215	4.2577~5.8890	5.1680 ~7.2277	3.4846~4.9958
WA	1.2545~1.4368	2.6065~5.4755	3.2771 ~7.6832	3.9033~9.5977	2.8637~6.9713

TABLE VII. THE SCOPE OF ECCENTRIC SHAFT AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2644~1.3277	3.0769 ~3.9559	3.9109~5.2521	4.6441~6.4544	3.2241~4.1031
KF	0.6764 ~1.2997	1.9016~3.7578	2.5240~4.8932	3.0953 ~5.9231	1.9544~3.6457
MAF	1.2874~1.3015	3.4807~3.7560	4.4951~4.8888	5.4180 ~5.9202	3.4821 ~3.6531
WA	1.2691~1.3274	3.1001~3.9400	3.9549 ~5.1080	4.7209~6.2105	3.2676~3.9021
LSM	1.2812~1.3259	3.4397~ 3.8347	4.4132~5.0719	5.2884~6.2028	3.4407~3.8549

TABLE VIII. THE SCOPE OF CRACKED SHAFT AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2467~1.3174	2.3342 ~4.5670	2.9101~ 5.9884	3.4182~7.3012	3.5065~4.0086
KF	0.6615 ~1.2998	1.9430~3.8181	2.5220~4.9550	3.0330 ~5.9685	1.9218~3.7903
MAF	1.2821~1.2992	3.2374~3.8550	4.1640~5.0093	4.9970 ~6.0402	3.6141 ~3.8079
WA	1.2608~1.3158	2.6100~4.3543	3.3023 ~5.6884	3.9226~6.9141	3.5626~3.9947
LSM	1.2809 ~1.3043	3.1871~ 4.2926	4.0980~5.5727	4.9149~6.7397	3.6127~3.7950

TABLE IX. THE SCOPE OF NO-SYMMETRY SHAFT AFTER FOUR FILTERING (ACCELERATION)

Filtering Method	Waveform Index S_f	Peak Index C_f	Pulse Index I_f	Margin index CL_f	Kurtosis index K_v
Real data	1.2829~1.3349	3.1001 ~4.5470	3.9771~6.0672	4.7788~7.4463	3.3366~4.6789
KF	0.6763~1.3221	1.7551~3.7085	2.3290~4.8916	2.8368 ~5.9753	1.9939~4.0890
MAF	1.3083~1.3212	3.3522~3.7158	4.3918~4.9046	5.3439 ~5.9894	3.6791 ~4.1198
WA	1.2900~1.3348	3.1031~4.3261	4.0187 ~5.7585	4.8673~7.0673	3.3952~4.4874
LSM	1.3086 ~1.3307	3.3279~ 4.1794	4.3590~5.5568	5.2959~6.8017	3.7714~4.4182

able to join in the constraints of time domain and frequency domain.

VI. CONCLUSIONS

For petrochemical rotating machinery fault exists the following problems: (1) the scope of dimensionless indicators is difficult to determine. (2) Process of transferring data collected from the scene to a remote server, disturbed by various factors, causing transmission errors, large fluctuations in the calculation of rotating machinery fault dimensionless index , resulting in a wide range of fault zone; In order to reduce error and narrow the scope of the rotating machinery fault interval. In this paper, dimensionless index combine with four kinds of filtering method to realize signal filter, excluding outliers and narrow the scope of the fault interval, but still there is the scope of normal equipment dimensionless index and fault equipment dimensionless index and the scope of the rotating machinery fault interval is difficult to distinguish, require further study.

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