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Online Bearing Fault Diagnosis Based on a Novel Multiple Data Streams Transmission Scheme

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ABSTRACT Bearing faults are the most common failure modes in the rotating system. Vibration data from the rotating system carry important information, that is, characterization and diagnosis; therefore, the vast vibration signals collected from multiple sensors mounted in different sites are transmitted in a certain order for online fault diagnosis. However, due to the influence of transfer paths and noises, the sensitivities to the same fault signal of measured data streams are of significant differences, and signals containing weak sensitivity to the fault are likely to be transmitted preferentially while neglecting transmission order. Meanwhile, high volume vibration data greatly increase the transmission burden. These above-mentioned reasons dramatically reduce online diagnostic efficiency. Thus, fully considering the sensitive differences to the fault for multiple channels, how to transmit measured data streams of multiple sensors for timely online detecting the bearing failure is still a primary challenge. In order to solve this problem, a novel online bearing fault diagnosis method based on the multiple data streams transmission schemes (MDSTS) is proposed in this paper. Multiple sensors are numbered consecutively, and data streams from all channels are transmitted according to the preset order and transport protocol via a certain length at the beginning of diagnosis. Then, a fault sensitivity assessment model (FSAM) is established on maximum mean discrepancy (MMD) for transmitting the most sensitive data stream by calculating the distribution discrepancies between each channel's data streams and the historical datasets in the frequency domain, and then, the fault diagnosis model based on K-nearest neighbor (KNN) trained on historical datasets was used to evaluate the transmission scheme and acquire reliable diagnostic results via predicting performances of multiple and consecutive datablocks until all these exceed an alarm value. The extensive experiment results show that the proposed method can timely and accurately identify the bearing faults and outperforms obviously competitive approaches.

INDEX TERMS Fault diagnosis, vibration signal, multiple data streams, transmission scheme.

I. INTRODUCTION

Rolling element bearings are among the most critical components and easily damaged in rotating machinery, the operation status of which is directly related to the operation of machinery or even to economical losses and human casualties [1]–[3]. Thus, it has a very high practical value to timely achieve accurate diagnosis and recognition of rolling bearing fault.

Cracks or spalls on the surfaces of the roller, outer race or inner race are commonly failure modes in bearings [4]. Bearing vibration signals contain a wealth of information about mechanical health status, which make it possible to extract the dominant features that characterize mechanical health through signal processing techniques [5]. Such as discrete cosine transform [6], wavelet transform [7] and empirical mode decomposition [8]. Currently, many vibration-based off-line diagnostic methods have already achieved significant success in the field of fault diagnosis. In [9], several selected and relevant features have been used to diagnose faults via performing indicators ranking according to a filter evaluation. Impulse components based on Graph Fourier Transform as the features of vibration signals to diagnose faults of rolling bearings [10]. Cerrada *et al.* [11] established a fault diagnosis model based on genetic algorithm and random forest. However, for the same fault in most fault diagnosis methods,

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sensors installed in different positions will inevitably receive different vibration signals due to the influence of transfer paths, and the sensitivities of measuring points to fault signals are different, which leads to larger differences of diagnostic performances for different sensors.

More recently, some scholars have been working on the sensitive measuring points of vibration signals, and have made some important progress in the fault diagnosis field. In [12], position optimization of sensors method based on bond graph to digraph transformation for the small modulus gear life experiment of a spacecraft was proposed. Mobed *et al.* [13] integrated the magnitude ratio and the fault evolution sequences and proposed an optimization algorithm for sensor location, type and number. The above research on the sensitive measuring points concentrated upon the sensor location optimization of the complete machine, and the impact from sensitivities of measuring point to fault diagnosis still exists. Meantime, increasingly complex mechanical structure leads to limitation of sensor installation sites in real-world. More specifically, taking the roller bearing online fault diagnosis problem as an example, once a local fault occurs, measured data from the rotating system will contain a wealth of information of the fault bearings. However, due to the influence of transfer paths and noise, the sensitivities to the fault signal of mass measured data from multiple channels are of obvious differences. Transmitting different channel's collected data via a fixed order without considering the differences of fault sensitivity is likely to cause that data streams containing weak sensitivity to fault are transmitted preferentially for online diagnosis, and high volume measured data from different channels greatly increases transmission burden, which dramatically reduce diagnostic efficiency. Thus, fully considering the sensitive differences to the fault for multiple channels, how to transmit collected data streams from known measuring points is the key point to timely online detect the bearing failure and there is still plenty of room for improvement.

In this paper, considering rapid detection, we proposed a novel online multiple data streams transmission scheme(MDSTS) for online bearing fault diagnosis. Multiple sensors are numbered consecutively, and data streams from all channels are transmitted according to the preset order and Transmission Control Protocol/Internet Protocol(TCP/IP) via a certain length at the beginning of diagnosis. Then, fault sensitivity assessment model(FSAM) is established on maximum mean discrepancy(MMD) for selecting the sensitive data stream by calculating distribution discrepancies between each channel's data streams and the historical datasets in frequency domain, and data stream that is of the smallest distribution difference will be transmitted preferentially in the next round until transmit data reach the preset size, and then, fault diagnosis model based on K-nearest neighbor trained on historical data was used to evaluate transmission scheme and acquire reliable diagnostic results via predicting performances of multiple and consecutive datablocks until all these exceed an alarm value.

The rest of this paper is organized as follows. Section II sketches out previous works and preliminaries, including maximum mean discrepancy and the K-nearest neighbor (KNN) algorithm. Section III introduces online fault diagnosis using multiple data streams transmission scheme, including fault sensitivity assessment model and multiple data streams transmission scheme and online diagnosis. Section IV presents the experimental evaluations. The conclusion are given in Section V.

II. PREVIOUS WORKS AND PRELIMINARIES

A. MAXIMUM MEAN DISCREPANCY

Note that when the machinery faults occur, the vibration signals of machines will be different from those of normal cases, where the changes can be easily characterized by features of machine signals [14]. Statistically distribution differences between fault signals and normal cases are obvious. In order to void expensive distribution calculation caused by the parametric criteria, a nonparametric distance metric, known as MMD, is employed for domain adaptation in our work. Taking historical dataset X_{hd} and transmitted data X_{te}, the MMD calculates the empirical estimate of distances across two sets of data in the p-dimensional embedding [15], [16]:

$$MMD(X_{hd}, X_{te}) = ||\frac{1}{n_{hd}}\sum_{i=1}^{n_{hd}} A^T x_i - \frac{1}{n_{te}}\sum_{j=1}^{n_{te}} A^T x_j||^2 \tag{1}$$

where $MMD(X_{hd}, X_{te})$ is the distance of distributions across two sets of data, A is the adaptation matrix, and n_{hd} and n_{te} denote number of historical instances and transmitted instances, respectively. $i = \{1, \cdots, n_{hd}\}$ and $j = \{1, \cdots, n_{te}\}$.

B. K-NEAREST NEIGHBOR ALGORITHM

Instance based learning or lazy learning which trains the classifier function locally by majority vote of its neighboring data points. KNN collects all available data points and classifies new data points based on similarity measure [17], [18]. The core idea of KNN algorithm is to assign new unclassified data points to the class to which the majority of its K nearest neighbors belongs. The process of KNN is outlined as follows:

(1) Given a test data stream x, and find the K nearest neighbors of x among all training data from historical data.
(2) Score the category candidates based on the category of K neighbors by calculating the similarity between the test data stream x and each neighbor data, which is denoted as $sim(x, tr_i)$.
(3) Calculate the sum of the similarity scores which belong to the same category, and then sort the scores of the candidate categories in descending order. Finally, assign the candidate category with the highest score to the test data stream x, which is expressed as follows:

$$f(x, C_j) = \sum_{tr_i \in KNN} sim(x, tr_i) Z(tr_i, C_j) \tag{2}$$

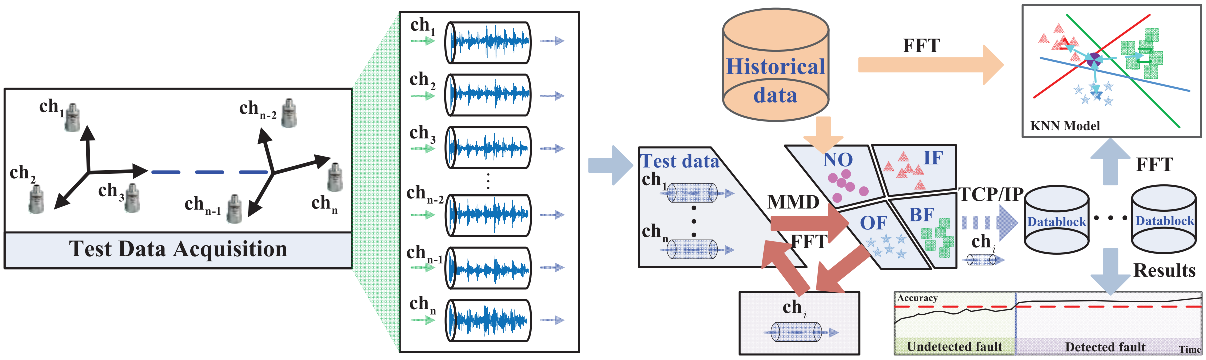

FIGURE 1. The framework of a novel multiple data streams transmission scheme for online bearing fault diagnosis.

where $Z(tr_i, C_j)$ is the value of the training data tr_i with respect to C_j.

KNN depends on the number of the nearest neighbor. There is no solution to find the optimal K and its value is completely up to user. Generally after some trials a K value is selected based on the best result and in a general way K is set to 1 [17]. Similarity measurement is primarily concerned with distance calculation, and most known distance measurements like Euclidean and Manhattan distances are used. In our work, according to experience [17], we set $K = 1$ and Euclidean distance is chosen for similarity measurement.

III. ONLINE FAULT DIAGNOSIS BASED ON MULTIPLE DATA STREAMS TRANSMISSION SCHEME

As mentioned in Section 1, due to the interference of different transfer paths and environmental noise, data streams from multiple sensors will be of different sensitivities to the same fault signal, and once data streams containing weak sensitivity to the fault are transmitted preferentially, which directly leads to poor performance of online bearing fault diagnosis. In order to solve this problem, a novel data streams transmission scheme is presented for online fault diagnosis in this section. The framework of our method is illustrated in Figure 1. FSAM is established on MMD for transmitting the most sensitive data stream by calculating distribution discrepancies between each channel's data stream and the historical datasets in frequency domain, and then, a fault diagnosis model based on historical data via KNN was used to diagnose bearing failures until multiple consecutive preset sized datablocks are detected beyond an alarm value. Details of each part are elaborated in the following subsections.

A. FAULT SENSITIVITY ASSESSMENT MODEL

Raw time series vibration signals are readily available and abound in bearing information. Due to the rotating nature of raw vibration signals from a defective bearing, the periodic impulse would appear in obtained signals once a fault occurs, and these fault impacts can be easily detected in frequency domain. Thus, the fast Fourier transformation (FFT) is conducted to process data streams being transmitted.

In our work, we directly online catch time domain waveforms from the raw time series vibration signals sampled from multiple sensors on site. These signals are transmitted to upper computer according to the preset order using TCP/IP at the beginning of diagnosis, and then, the fault sensitivity assessment model is established by using MMD based on frequency amplitudes for avoiding interference of phase fluctuation caused by sensor installation site. The main steps of fault sensitivity assessment model are as follows:

- **Step 1**: Test data streams X_{rt}^k collected from a kth channel are transmitted to upper computer via TCP/IP with a certain length, and catch frequency amplitudes from above test data streams by performing FFT: $X_{te}^k = \{x_{tei}^k \in R^{d\times 1} | i = 1, \ldots, n_{te}, k = 1, \ldots, n_{ch}\}$, where n_{te} and n_{ch} are the number of test data streams and channels respectively. d is the number of amplitudes in frequency domain.
- **Step 2**: Randomly select n_{hd} samples from the historical dataset and obtain frequency amplitudes via FFT as a training dataset $X_{hd} = \{x_i \in R^{d\times 1} | i = 1, \ldots, n_{hd}\}$, where n_{hd} is the number of training samples.
- **Step 3**: Calculate the distribution differences between historical dataset and test data streams collected from each channel in order by using MMD:

$$\begin{aligned} D = \{D_k = \|\frac{1}{n_{hd}}\sum_{i=1}^{n_{hd}} I^T x_i \\ -\frac{1}{n_{te}}\sum_{j=1}^{n_{te}} I^T x_j^k\|^2 | k = 1, \ldots, n_{ch}\} \\ = \{D_k = tr(I^T X_k M X_k T I) | k = 1, \ldots, n_{ch}\} \end{aligned} \quad (3)$$

It has been shown that Where I and n_{ch} represent the identity matrix and number of channels respectively, and $tr(\cdot)$ denotes the trace of a matrix. $X_k = \{X_{hd}, X_{te}^k\} \in R^{d\times(n_{hd}+n_{te})}$. M is MMD matrix and is computed as follows [19]

$$M = \begin{cases} \frac{1}{n_{hd}n_{te}}, & x_i, x_j \in X_{hd} \\ \frac{1}{n_{hd}n_{te}}, & x_i, x_j \in X_{te}^k \\ \frac{-1}{n_{hd}n_{te}}, & otherwise \end{cases} \quad (4)$$

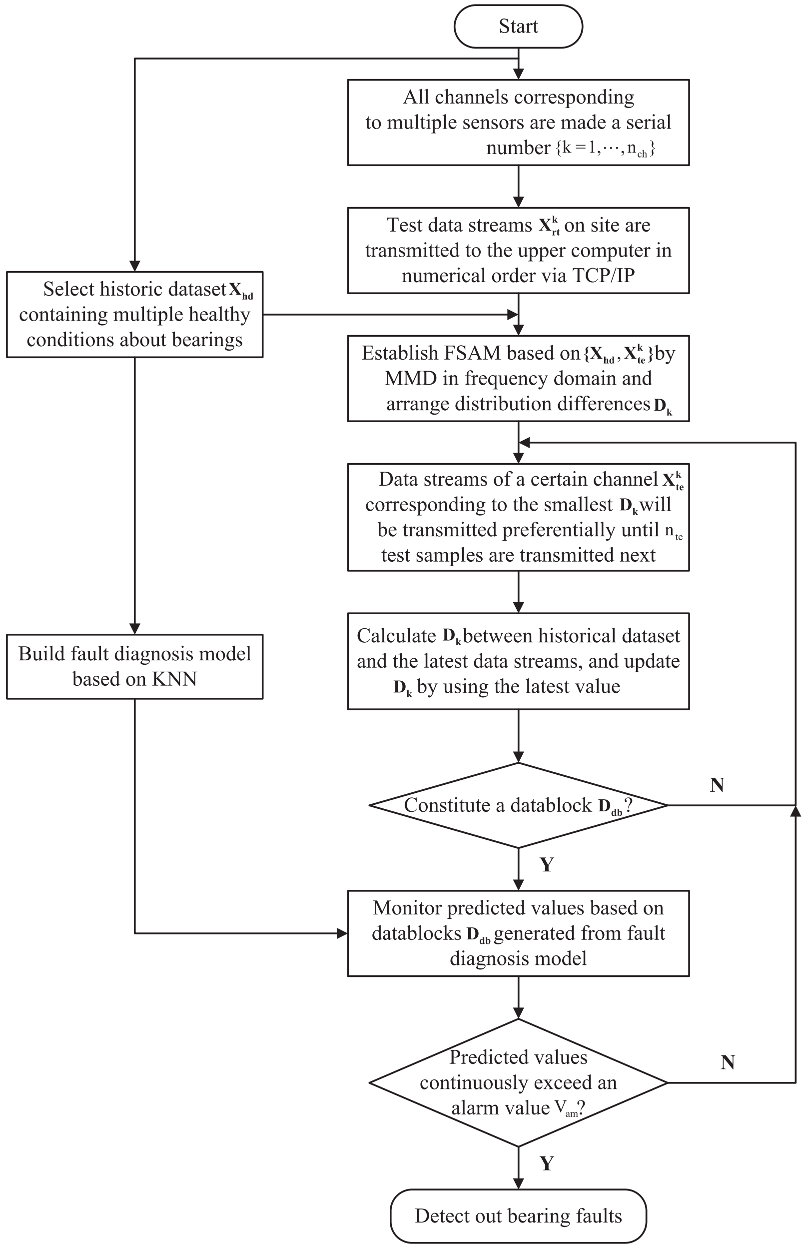

FIGURE 2. Flow chart of online fault diagnosis based on multiple data streams transmission scheme.

Finally, fault sensitivity assessment model is established by D.

B. MULTIPLE DATA STREAMS TRANSMISSION SCHEME AND ONLINE DIAGNOSIS

In order to timely diagnose bearing faults, signals containing the most sensitivity to the fault from a certain channel are transmitted preferentially based on FSAM until detect faults. The essence of FSAM is distribution differences D between historical dataset and test data established by using MMD. Once a fault occurs, the healthy condition of bearings is determinate and the data distribution is also determinate. If the distribution differences D_k is the smallest, then the test data distribution is the most close to historical dataset, and it also means that the sensitivity to the fault of D_k is the most sensitive. Thus, data streams of kth channel corresponding to the smallest D_k will be transmitted preferentially. The details of multiple data streams transmission scheme are as follows:

- **Step 1**: At the beginning of transmission, all channels corresponding to multiple sensors are made a serial number based on $\{k = 1, \ldots, n_{ch}\}$ corresponding to associated channels, and test data streams on site are transmitted to the upper computer in numerical order.
- **Step 2**: Distribution differences D are obtained based on FSAM according to the serial number in **Step 1** and $D_k \in D$ are arranged in ascending order.

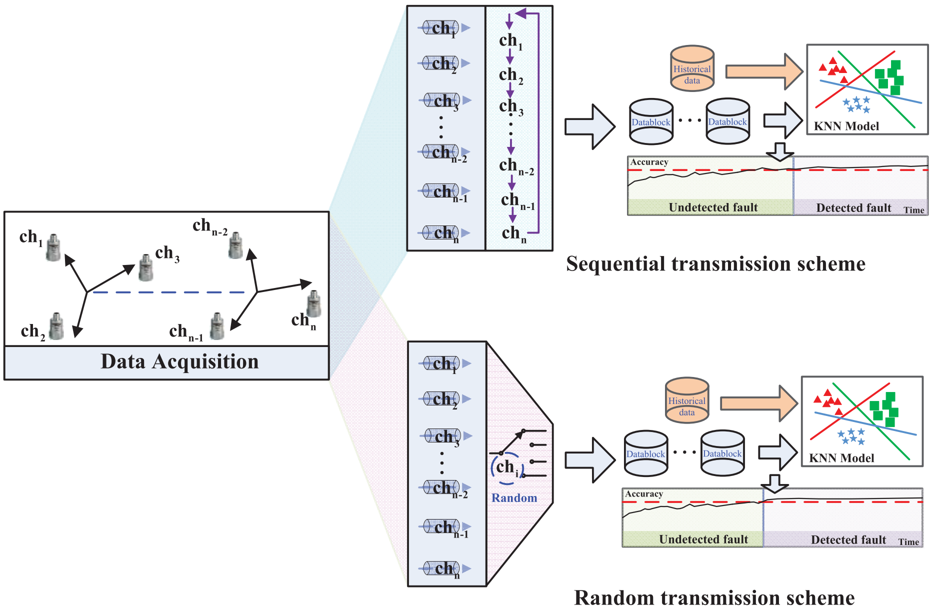

FIGURE 3. The framework of two conventional transmission schemes for online fault diagnosis.

- **Step 3**: Data streams of kth channel corresponding to the smallest D_k will be transmitted preferentially until n_{te} test samples are transmitted next.
- **Step 4**: Calculate distribution differences D_k between historical datasets X_{hd} and the latest data streams X_{te}^k based on FSAM, and update D_k via the latest value, and then, $D_k \in D$ are rearranged in ascending order. Next, go to **Step 3.**

Timely and accurate diagnosis is the key point for transmission scheme and online diagnosis. In order to evaluate transmission scheme and acquire reliable diagnostic results, an evaluation criterion is embedded in online diagnosis. A datablock $D_{db} = \{X_{te}^k | k = 1, \ldots, n_{db}\}$ that is a collection containing transmitted data streams is used to preprocess and detect bearing faults, where $n_{te} \times n_{db}$ is number of transmitted data streams in a datablock. Considering inherent simplicity and the robustness to noisy training data, KNN is selected as best method for building the fault diagnosis model. Diagnostic results based on multiple and consecutive datablocks all exceed an alarm value, then transmission and online diagnosis are completed. Whether it can detect bearing faults for online diagnosis is defined as transmissive detection cost C_{dc}. In addition, time cost resulting from entire process that beginning at the start of transmission and ending at the completion of transmission is defined as transmissive time cost C_{tc}, and the number of datablock when transmission and diagnosis are completed is defined as transmissive data volume cost C_{dv}. The error of computational accuracy is defined as A_{ca}, and its format is: average $\pm$ standard deviation. Average accuracy is the average predicted value based on all transmissive datablocks. The details of this evaluation criterion embedded in online diagnosis are as follows:

- **Step 1**: Data preprocessing: Each signal sample being transmitted is converted into its corresponding frequency spectrum and FFT amplitudes are extracted as fault features. Further, frequency spectra of each time domain are normalized.
- **Step 2**: The final preprocessed training datasets X_{hd} including multiple healthy conditions of bearings are used for training fault diagnosis model by using KNN.
- **Step 3**: A datablock D_{db} generated by multiple data streams transmission scheme is selected to detect bearing faults via the fault diagnosis model.
- **Step 4**: Monitor predicted values based on datablocks, and bearing faults are detected when predicted values of multiple and consecutive $q = 5$ datablocks D_{db} all exceed an alarm value V_{am}, and record C_{tc} and C_{dv}.

The flow chart of online fault diagnosis based on multiple data streams transmission scheme is shown in Figure 2.

IV. EXPERIMENTAL EVALUATIONS

In order to verify the effectiveness of the proposed online fault diagnosis method, a bearing test rig for data collection and online diagnosis are used. The proposed method is compared with two conventional approaches illustrated in Figure 3.

a. Sequential transmission scheme (STS): All channels corresponding to multiple sensors are numbered and data streams are transmitted according to numbers. In our experiment, the transmitted order is index descending order of channels. Finally predicted values from fault diagnosis model based on KNN and datablocks are monitored.

b. Random transmission scheme (RTS): All channels corresponding to multiple sensors are numbered and draw a data stream from a channel at random to transmit. In final, predicted values from fault diagnosis model based on KNN and datablocks are monitored.

A. EXPERIMENTAL SETUP AND DATASET PREPARATION

The test-bed shown in Figure 4 consists of an electric motor, a transducer, a belt, a tachometer, eight accelerometers, an acquisition instrument and two computers. One of the bearings without defects is located in the bearing housing installed into the idler closer to the motor. The other bearing is located in the bearing housing installed into the idler farther to the motor, and it could be replaced by the test bearings [16]. Subjected to wire-electrode cutting, inner-race faults (IF), outer-race faults (OF) and ball fault (BF) are introduced into the test bearing. The vibration signals are sampled with the help of eight accelerometers installed as illustrated in Figure 4.

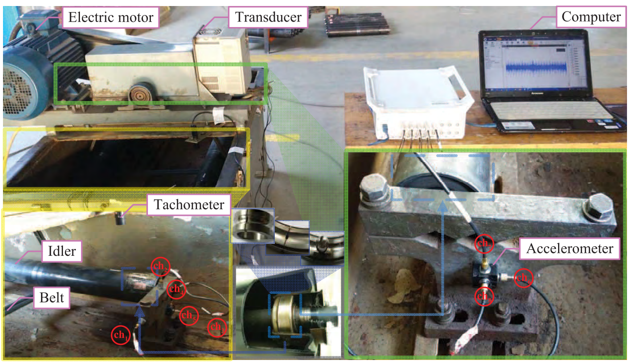

FIGURE 4. Bearing test rig of the belt conveyor idler.

For purpose of simulating the actual application and making the experimental results more persuasive, in our experiment, raw vibration signals are collected from eight sensors and sampled at a frequency of 20kHz on site, and transmitted to the upper computer via TCP/IP with a certain length at 8192 data points. The type of the used bearings is 6204, and its main parameters are presented in Table 1.

TABLE 1. Main parameters of 6204 ball bearing.

Type	Inner race diameter(mm)	Outer race diameter(mm)	Number of balls	Bearing width(mm)	Balls diameter(mm)
6204	20	47	8	14	7.9

Four healthy conditions of bearings, i.e., NO(normal bearings), IF, OF and BF, are considered and each fault type of vibration data is obtained from four kinds of working conditions, i.e., L1 = 1797 rpm, L2 = 1772 rpm, L3 = 1750 rpm and L4 = 1730 rpm. Figure 5 shows the time waves and corresponding the spectrums of a normal bearing and faulty bearings under the condition of L4. From the results in Figure 5, it is clear that spectral structures are of significant differences for different healthy conditions of bearings. Historic datasets contain all above healthy conditions of bearings and each fault includes 200 samples.

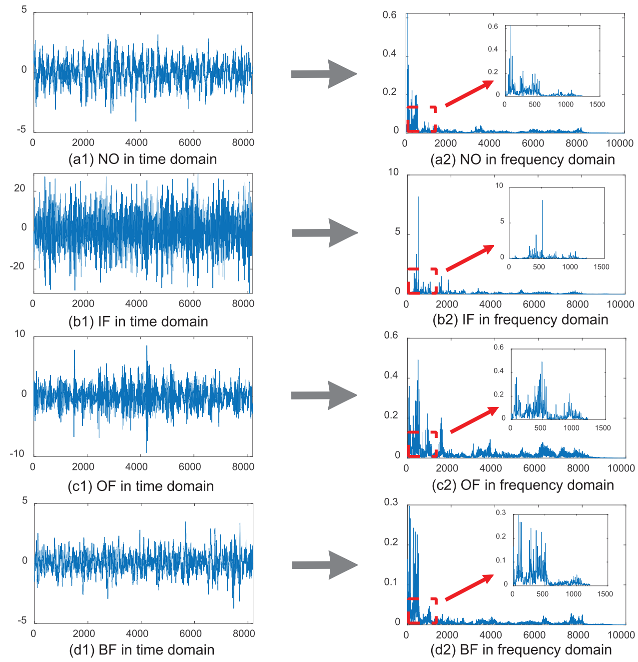

FIGURE 5. Time waves and spectrums with different healthy conditions under the condition of L3.

Each sample contains 4096 Fourier coefficients transformed from the raw vibration signals via FFT. During establishing FSAM, n_{te} is selected 5 for investigating diagnostic results. A datablock consists of $n_{db} = 20$ test samples and it is identified as the bearing fault when $q = 5$ predicted values exceed $V_{am} = 95\%$ set based on a 2-sigma-limited Gaussian distribution.

In order to demonstrate the effectiveness of MDSTS, contrast methods of a-b are also carried out simultaneously. In all, 36 different tests are conducted and the description of experimental setup in detail is shown in Table 2.

TABLE 2. Description of the experimental setup.

Method	♯ of test	Fault type	Working condition
	1	IF	L1, L2, L3, L4
STS	2	OF	L1, L2, L3, L4
	3	BF	L1, L2, L3, L4
	4	IF	L1, L2, L3, L4
RTS	5	OF	L1, L2, L3, L4
	6	BF	L1, L2, L3, L4
	7	IF	L1, L2, L3, L4
MDSTS	8	OF	L1, L2, L3, L4
	9	BF	L1, L2, L3, L4

B. DIAGNOSIS RESULTS OF THE PROPOSED METHOD

The diagnositic results for three transmission schemes are shown in Figure 6, Figure 7, Figure 8 and Figure 9, and the sensitivities to faults of different channels are illustrated by using t-SNE [20] based on frequency amplitudes in Figure 10.

Each figure is composed of nine subfigures under a certain working condition. The left of the symbol "−" in every

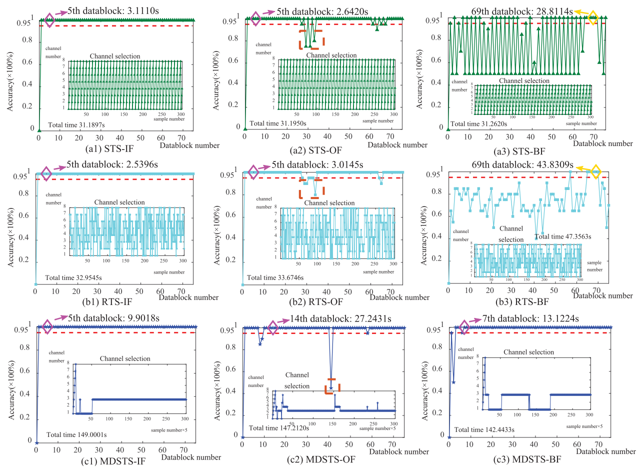

FIGURE 6. The results with different faults under the condition of L1.

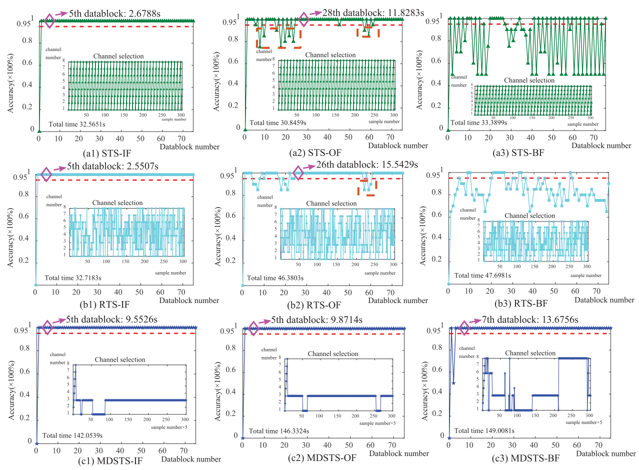

FIGURE 7. The results with different faults under the condition of L2.

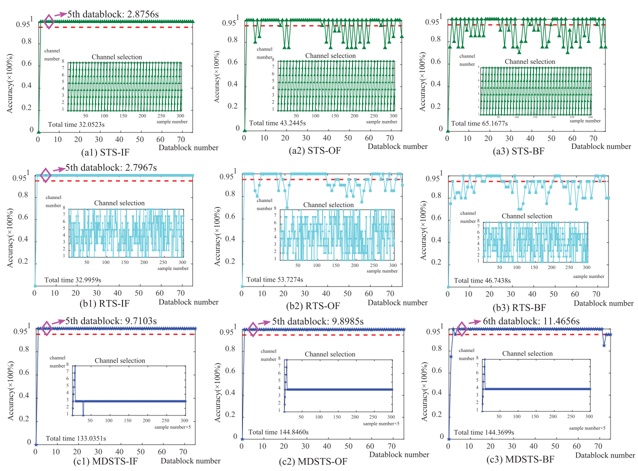

FIGURE 8. The results with different faults under the condition of L3.

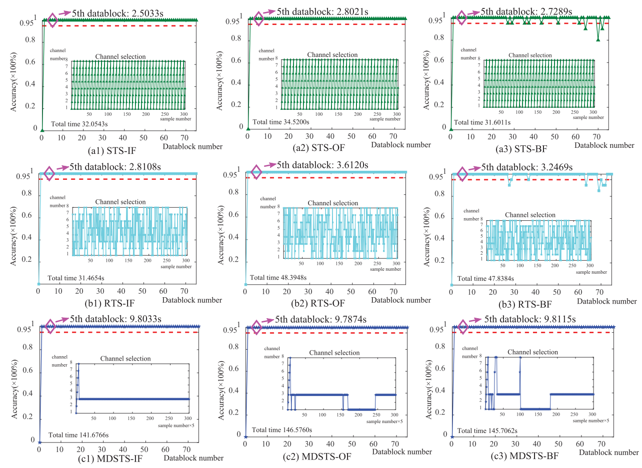

FIGURE 9. The results with different faults under the condition of L4.

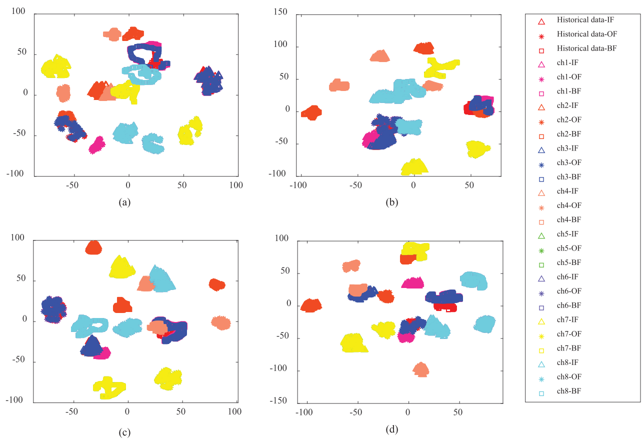

FIGURE 10. Sensitivities to faults under different conditions.

subfigures represents the transmission scheme and the right represents fault type for diagnosing. The $x - axis$ of the subfigure is the number of transmitted datablocks, and the $y - axis$ is detection accuracy for a datablock. In each subfigure, an embedded figure refer to channel selection during the transmission process. The $x - axis$ of the embedded figure represents the serial number and the $y - axis$ is the number of data streams.

From the performances of transmission schemes for online bearing fault diagnosis in Figure 6, 7, 8 and 9, it is obvious that bearing inner fault can be efficiently detected online when the fifth datablock is transmitted for these three method, and time cost of MDSTS is higher than other two compared methods. Due to the establishment of fault sensitivity assessment model, this phenomenon is reasonable theoretically. We can obviously find that performance of STS and RTS are all significantly unstable (marked with $*$ in Table 3) when bearing outer fault occurs. Overall speaking, the performances of RTS are slightly better than STS's. For example, in subfigures (a2) and (b2) from Figure 6, although it can be marginally feasible for detecting outer fault, there are always predicted values below the preset alarm value from time to time. This situation is more serious and online diagnosis is failure in Figure 8 when using STS and RTS. For bearing

TABLE 3. Detailed performances of different transmission schemes for online fault diagnosis.

Transmitted data		STS C_{dc}	STS C_{dv}	STS C_{tc}	RTS C_{dc}	RTS C_{dv}	RTS C_{tc}	MDSTS C_{dc}	MDSTS C_{dv}	MDSTS C_{tc}
L1	IF	Y	5th	3.1110s	Y	5th	2.5396s	Y	5th	9.9018s
	OF	Y^*	5th	2.6420s	Y^*	5th	3.0145s	Y	14th	22.2431s
	BF	N	>75th	>31.2621s	N	>75th	>47.3536s	Y	5th	9.9018s
L2	IF	Y	5th	2.6788s	Y	5th	2.5507s	Y	5th	9.5526s
	OF	N	>75th	>30.8459s	N	>75th	>46.3803s	Y	5th	9.8714s
	BF	N	>75th	>33.3899s	N	>75th	>47.6981s	Y	7th	13.6756s
L3	IF	Y	5th	2.8756s	Y	5th	2.7967s	Y	5th	9.7103s
	OF	N	>75th	>65.1677s	N	>75th	>46.7438s	Y	6th	11.4656s
	BF	N	>75th	>31.2621s	N	>75th	>47.3536s	Y	5th	9.9018s
L4	IF	Y	5th	2.5033s	Y	5th	2.8108s	Y	5th	9.8033s
	OF	Y	5th	2.8021s	Y	5th	3.6120s	Y	5th	9.7874s
	BF	Y^*	5th	2.7289s	Y^*	5th	3.2469s	Y	5th	9.8155s

TABLE 4. Computational accuracy errors of different transmission schemes for online fault diagnosis.

Transmitted data		STS A_{ca}	RTS A_{ca}	MDSTS A_{ca}
L1	IF	100	100	100
	OF	98.67±4.82	99±3.18	98.87±6.65
	BF	76.73±23.94	75.13±12.94	99.2±5.81
L2	IF	100	100	100
	OF	97.73±5.94	98.07±4.34	100
	BF	82.2±21.03	84.07±10.12	99.33±5.77
L3	IF	100	100	100
	OF	94.67±9.17	94.33±7.28	100
	BF	91.07±10.63	91.07±8.67	99.2±3.49
L4	IF	100	100	100
	OF	100	100	100
	BF	99±3.08	99.07±2.93	100

ball fault, STS and RTS does not work for online diagnosis in nearly all instance under the condition of L1, L2 and L3. Specifically speaking, most accuracies of detection for datablocks are only about 50% when using STS in Figure 6 and Figure 7 and a lots of predicted values stay at about 70% via RTS under the condition of L1 and L2. These results mentioned above indicate that STS and RTS cannot be applied to online high diagnostic efficiency. What is exciting that MDSTS is evidently superior to compared method. Whatever the conditions and fault types are, all faults can be diagnosed effectively within 10 datablocks, and the average diagnostic time is about 11.97s. Although a single shock appears when transmitting 41th datablock using channel 4 in (c2) from Figure 6, MDSTS can adjust the transmission scheme that transmitting data streams from channel 4 to channel 3 in time and predicted value is improved from 45% to 100% for the next datablock. Even for bearing ball fault, MDSTS can still be applied to online efficient diagnosis without any fluctuations among predicted values. According to embedded figures in (c1), (c2) and (c3) from Figure 6, 7, 8 and 9 and Figure 10, MDSTS will always transmit data streams containing the most sensitivity to faults preferentially. More details can be found in Table 3 below. Computational accuracy errors of different transmission schemes for online fault diagnosis are also shown in Table 4. Through above result analysis, we can conclude that MDSTS is a very potential transmission scheme for online bearing fault diagnosis compared other two conventional transmission schemes.

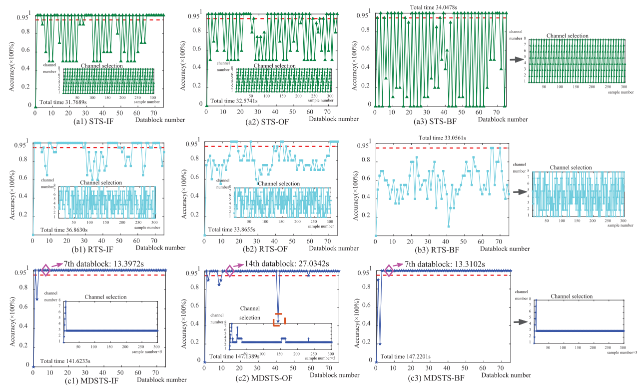

FIGURE 11. The results with different faults under the condition of L1 with noises.

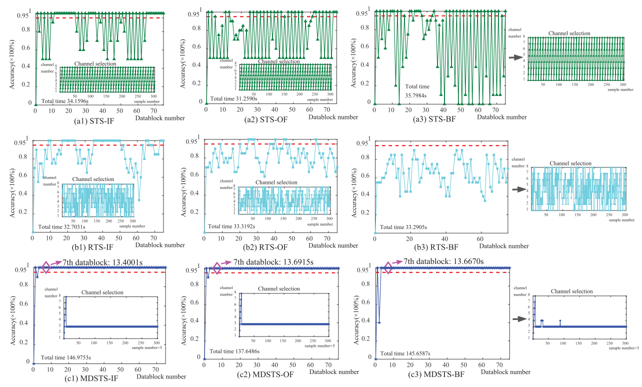

FIGURE 12. The results with different faults under the condition of L2 with noises.

C. EFFECT OF NOISES ON TRANSMISSION SCHEME FOR ONLINE FAULT DIAGNOSIS

In real cases, owning to the existence of strong noise in local area, vibration data sampled from the corresponding channels are recorded consists of low SNR [21], [22], which can be formed as follows:

$$SNR = 10log(\sigma_s^2/\sigma_n^2) \tag{5}$$

where σ_n^2 indicates the variance of noise response and σ_s^2 represents the variance of the signal. In order to match the reality, SNR with −30dB, −10dB and −5dB are added randomly to three different channels. In our experiment, SNR with −30dB, −10dB and −5dB are added respectively in channel 6, 8 and 1. Experiment settings are the same with ones in Table 2. The experimental results are shown in Figure 11, 12, 13 and 14, and the sensitivities to faults of different channels are illustrated by using t-SNE [20] based on frequency amplitudes in Figure 15.

From the results of transmission schemes in Figure 11, 12, 13 and 14, it is clear that data streams transmitted via STS and RTS are not applied to online bearing fault diagnosis. Due to the influence of strong noises in local area, the vast majority of diagnostic performances are only 50% and much less than the alarm value when using STS

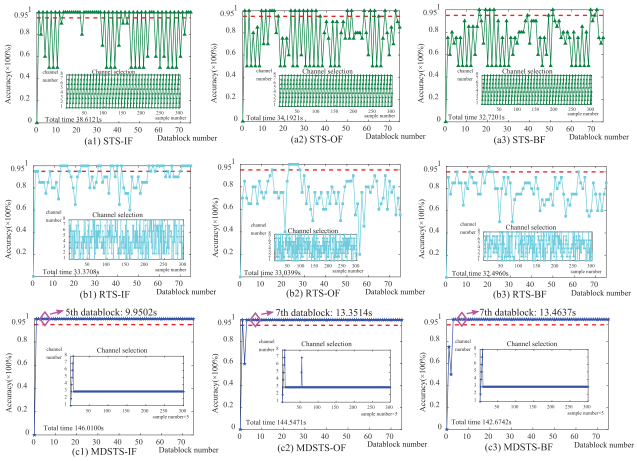

FIGURE 13. The results with different faults under the condition of L3 with noises.

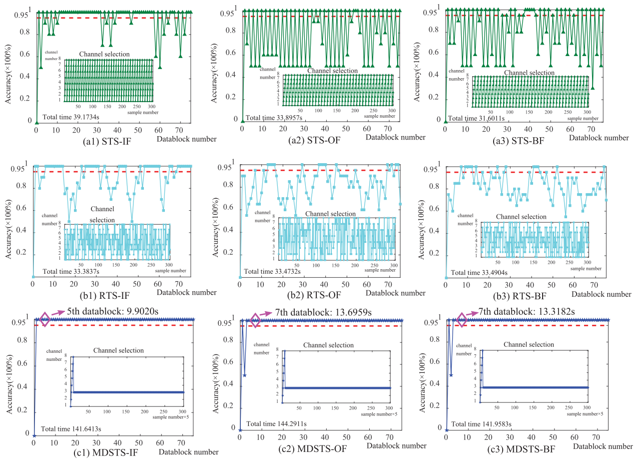

FIGURE 14. The results with different faults under the condition of L4 with noises.

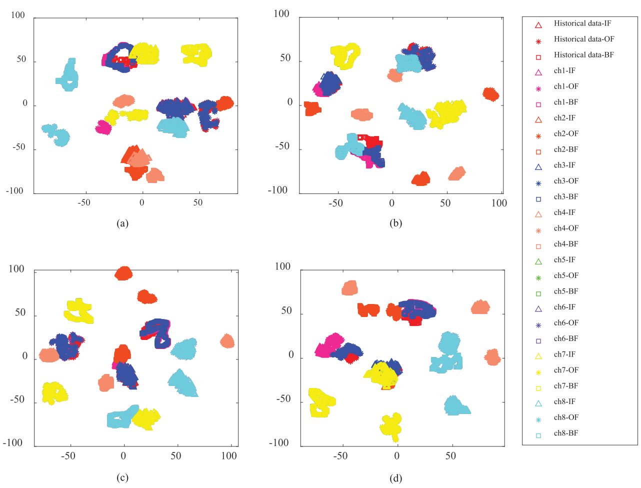

FIGURE 15. Sensitivities to faults with measurement noise in local area under different conditions.

in Figure 11, 12, 13 and 14, and similar results also are obtained when using RTS under all conditions. Especially in (a3) from Figure 11 and Figure 12, many data streams transmitted via STS are not detected ball faults at all. These results

TABLE 5. Detailed performances of different transmission schemes for online fault diagnosis under conditions of strong noises in local area.

Transmitted data		STS			RTS			MDSTS		
		C_{dc}	C_{dv}	C_{tc}	C_{dc}	C_{dv}	C_{tc}	C_{dc}	C_{dv}	C_{tc}
L1	IF	N	>75th	>31.7689s	N	>75th	>36.8630s	Y	7th	13.3972s
	OF	N	>75th	>32.5741s	N	>75th	>33.8655s	Y	14th	27.0342s
	BF	N	>75th	>34.0478s	N	>75th	>33.0561s	Y	7th	13.3102s
L2	IF	N	>75th	>34.1596s	N	>75th	>32.7031s	Y	7th	13.4001s
	OF	N	>75th	>31.2590s	N	>75th	>33.3192s	Y	7th	13.6950s
	BF	N	>75th	>35.7984s	N	>75th	>33.2950s	Y	7th	13.6670s
L3	IF	N	>75th	>38.6120s	N	>75th	>33.3708	Y	5th	9.9502s
	OF	N	>75th	>34.1921s	N	>75th	>33.0399s	Y	7th	13.3514s
	BF	N	>75th	>32.7201s	N	>75th	>32.4960s	Y	7th	13.4637s
L4	IF	N	>75th	>39.1734s	N	>75th	>33.3837s	Y	5th	9.9020s
	OF	N	>75th	>33.8957s	N	>75th	>33.4732s	Y	7th	13.6959s
	BF	N	>75th	>31.6011s	N	>75th	>33.4904s	Y	7th	13.3182s

TABLE 6. Computational accuracy errors of different transmission schemes for online fault diagnosis under conditions of strong noises in local area.

Transmitted data		STS	RTS	MDSTS
		A_{ca}	A_{ca}	A_{ca}
L1	IF	85.6±20.9401	91.8±11.84	99.6±3.46
	OF	79.47±21.88	80.87±11.64	98.73±6.73
	BF	56.73±44.54	58.27±16.47	98.8±9.29
L2	IF	88.53±18.72	87.33±14.41	99.87±1.15
	OF	77.2±22.18	81.8±11.05	99.87±1.15
	BF	68.87±38.73	65.53±14.18	99.2±6.93
L3	IF	86±20.66	90±10.10	100
	OF	77.47±19.58	74.13±14.71	99.47±4.62
	BF	74.47±16.7	78.47±11.54	99±6.42
L4	IF	94.67±11.89	90.67±13.06	100
	OF	80.53±22.41	82.93±13.23	99.33±5.77
	BF	82.2±20.99	83.33±11.78	99.33±5.77

fully illustrate that data streams obtained via conventional transmission schemes can not be applied to rapid diagnosis. What is worth mention, all data streams achieved by using the proposed method can be detected faults within 10 datablocks and the detection accuracies are almost 100% under all conditions for all fault types. Although a single shock also appears when transmitting 41th datablock using channel 4 in (c2) from Figure 11, MDSTS can rapidly change the channel of stream data transmission and diagnostic performance is raised to 100% for the next datablock. From all embedded figures under all conditions and Figure 15, MDSTS can active avoid channels added strong noises and select channels containing the most sensitivity to the fault for transmitting data streams. The details can be found in Table 5. Computational accuracy errors of different transmission schemes for online fault diagnosis are also shown in Table 6. Through above analysis, it can be concluded that the proposed method still can work effectively when certain noise exists in local area and the advantages are highlighted compared two conventional methods.

D. DISCUSSION

In many actual fault diagnosis and classification scenarios, due to the influence of transfer paths and noises, the sensitivities to the same fault signal of measured data streams show significant differences. In fact, sensitivity differences to the fault among different channels reflect the differences among data structures, and fault diagnosis is essentially to find similar data structures with fault signals. Thus, transmitting measured data streams that are of the most sensitivity to the fault is the key for timely online detecting bearing faults. MDSTS provides a novel transmission scheme for online fault diagnosis. There are still several remarks that need to be described.

(1) In our work, we propose a novel transmission scheme to transmit multiple sensors data for online bearing fault diagnosis. Diagnostic results based on data streams obtained via conventional transmission schemes fluctuate sharply or even these methods cannot be detected faults in Figure 6, 7, 8 and 9. To solve this problem, we present a new transmission scheme based on FSAM established by using MMD, channel selection trick and KNN. Finally, data streams achieved by the proposed method can be detected faults timely and detection accuracies almost can reach 100%. Compared with methods in subsection B from section IV, our method has obvious advantages.

(2) The results from experiments in subsection C from section IV indicate that MDSTS is more suitable to the situation that the presence of interference in local areas during acquisition of signals. It is almost impossible to detect faults timely based on data streams obtained by using STS and RTS while our method can detect all faults timely under all conditions by avoiding data streams with some interference and preferentially transmitting data streams that are of the most sensitivity to faults. Compared with STS and RTS, our method has absolute advantages.

V. CONCLUSION

In this paper, a novel transmission scheme for online fault diagnosis has been proposed. Data streams containing the most sensitivity to faults are transmitted preferentially by fault sensitivity assessment model, channel selection trick and K-nearest neighbor. The proposed method provides a novel perspective for rapid remote online machine condition monitoring, and it solves diagnostic inefficient problem of online diagnosis in the multisensor scenario. Different transmission experimental tests under variable working conditions demonstrated the effectiveness and feasibility of the proposed method.

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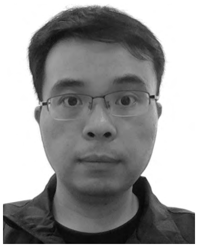

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