Best Time Domain Features for Early Detection of Faults in Rotary Machines Using RAT and ANN

Mohammed Al-SAAD (✉ Mohammed.kadom@uobasra.edu.iq)

University of Basrah <https://orcid.org/0000-0002-8061-4998>

MOHAMMED Al-Mosallam

University of Basrah

Ahmed Alsahlani

University of Basrah

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Best Time Domain Features for Early Detection of Faults in Rotary Machines Using RAT and ANN

Mohammed Al-Saad^{*}, Mohammed Al-Mosallam[†], Ahmed A. M. Alsahlani[‡]

^{*}Mechanical Department/Engineering College, Basrah University, Basrah, Iraq (mohammed.kadom@uobasrah.edu.iq)

[†]Mechanical Department/Engineering College, Basrah University, Basrah, Iraq (mohammed.mohsen@uobasrah.edu.iq)

[‡]Mechanical Department/Engineering College, Basrah University, Basrah, Iraq (Ahmed.mahdi@uobasrah.edu.iq)

Abstract

The common mechanical defect of rotating machinery is bearing failure which is considered the most common failure mode in rotating machinery. This kind of failure can lead to large losses as financial during work. Early detection of different faults in rotating machines such as bearing fault, misalignment, and others is considered one of the techniques in which is achieved by further signal processing techniques. Thus, using statistical methods such as reverse arrangement tests (RAT) to obtain the best a feature associated with these different faults is the perfect solution to find the failure which is widespread in the early detection of a fault. This type of feature will be used in Artificial Neural networks (ANN) as input for auto diagnosis. These characteristics are independently associated with different types of fault. Using RAT is considered very important in the process of linking different kinds of failures with the most important features.

Key word: RAT, ANN, Time domain feature, Rotating machine

1. Introduction

In recent time domain features were used in early fault detection methods. Some of the time domain (TD) features are extracted depending on the ability of these factors to detect faults [1], kosasih and et al [2] used a cumulative technique in order to estimate the degradation trend in features with time then the information about the deterioration of the slewing bearing is revealed. James and Walter [3] used an autoregressive model. The extracted features are established to obtain degradation trend, when faults occur in rotating machinery, the vibration signals could be changed [4]. The amplitude and distribution of the TD signals may be different from those of that normal condition. TD statistical factors have been used to detect the existence of the development of rotating machine damage [5]. Tsang [6] introduced a review on the best method used to detect the trend in data. These data are independently and identically distributed. Also, these data are promised to the null hypothesis. A Novel method introduced by [7] to integrating the Convolutional Neural Networks (CNNs) with the Variational Mode Decomposition (VMD) algorithms which named as “ Variational Mode Decomposition with Deep Convolutional Neural Networks (VMD-DCNNs)”, they described the method, in an end-to-end way, where they can realize the fault diagnosis of

rolling bearings during directly processes raw vibration signals without artificial experiences or manual intervention. [8, 9]. The used CM and FDD to diagnose faults and failures bearing element. Beck and et al. [10] examine the statistical test methods for assessing surface electromyography (EMG) signal stationary. One of these statistical methods is RAT. The hypothesis of randomness for each data set is tested using RAT [11]. Also, Murray and et al. [12] used RAT in pattern recognition problems. They are showed that the RAT has higher performance than the support vector machine. In this work, we will use the RAT method to estimate the trend in features and recognize the gradients that get in the data because of the presence of a certain fault in the machine. This novel method is used next for identifying and detecting faults in rotating machine.

Learning methods still the best method to machine fault detection such as ANN. Attaran [13] investigated the problem of automatic bearing fault diagnosis using machine learning methods. These methods consist of feature extraction, feature selection, and classification, they also concern on the TD statistical characteristic. There are also other development method uses to vibration signature analysis. Sumit [14] is introduced a review to recent development vibration signature analysis techniques.

2. Time Domain Features

The TD features which can be extracted from raw vibration signal are as following:

1. Mean Value

$$\text{Mean } \bar{x} = \frac{1}{N} \sum_{i=1}^N x(i) \dots \dots (1)$$

Usually, the mean value of a signal is of little use in vibration analysis. But it indicted to the vibration signal manner.

2. Root Mean Square (RMS)

This feature gives good results in tracking the overall vibration level in the signal [14]. Calculating the RMS value from formula [15]:

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N x(i)^2} \dots \dots \dots (2)$$

3. Standard Deviation, SD

It is a measure of the dispersion about the mean. The standard deviation is defined as:

$$\text{SD, } \sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^2} \dots \dots (3)$$

4. Kurtosis

It provides a measure of the size of the tail of a distribution and can be used as an indicator of major peaks in the data set. Kurtosis is given by [16], [17]:

$$\text{Kur} = \frac{\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^4}{\sigma^4} \dots \dots (4)$$

5. Skewness

Skewness (SK) is a commonly used parameter when analyzing dynamic signals; SK is defined by [16],

$$\text{SK} = \frac{\frac{1}{N} \sum_{i=1}^N (x(i) - \bar{x})^3}{\sigma^3} \dots \dots (5)$$

The SK Value is more sensitive to an asymmetry in the large values in the x than the mean, due to that the value of x raised to third power.

6. Peak Value

It is a sure indication for some component deterioration. The PV is defined by [17], [18] as:

$$\text{PV} = \frac{1}{2} (\max(x(i)) - \min(x(i))) \dots \dots (6)$$

7. Shape Factor

Shape factor SF is defined as the ratio of the RMS to mean value. It represents changes under unbalance and misalignment[18].

$$\text{SF} = \frac{\text{RMS}}{\frac{1}{N} \sum_{i=1}^N |x(i)|} \dots \dots \dots (7)$$

8. Impulse Factor

The impulse factor (ImF) which is also found to be an indicator of bearing faults is defined as the ratio of the peak value to mean value of the time signal [17].

$$\text{ImF} = \frac{\text{Peak}}{\frac{1}{N} \sum_{i=1}^N |x(i)|} \dots \dots \dots (8)$$

9. Clearance Factor (CF)

It is another time domain feature, which can estimate by [17],

$$\text{CF} = \frac{\text{Peak}}{\frac{1}{N} (\sum_{i=1}^N \sqrt{|x(i)|})^2} \dots \dots (9)$$

10. Crest Factor

The aim of the CF calculation is to give a quick idea of how much impacting is occurring in a waveform. Impacting is often associated with roller bearing wear, cavitations and gear tooth wear. The CF is one of the important features that can be used to trend machine Condition [19]. CF is given below as [16]:

$$\text{CrF} = \frac{\text{Peak}}{\text{RMS}} \dots \dots \dots (10)$$

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

3. RAT In Features Trend and Selection

The features are changed with machine healthy state. In many applications, degradation of bearing conditions is usually monitored by changes in time-domain features. The extracted features show accurate information about the incipient of fault as compared to the extracted features from the original vibration signal [2]. The feature of defect bearing is larger in magnitude than the healthy bearing and shows a gradual upward trend and variance increase [11]. This section also will use a formalist statistical test. This test is particularly good in detecting monotonic (i.e. gradual and continuing) trends in the data. The existence of these trends also indicates non-randomness. The test was developed by Bendat and Peirsol [19] and is a well-known accurate test of randomness. The RAT is a hypothesis test

that detects if there is a trend in the measured parameter [19]. The test procedure is as follows:

Firstly, the sampled time sequence of a signal $x(t)$ of length $M \times N$, M times of measurements, N the Number of samples in each measurement. The sequence is divided into N segments. These segments are used for calculating the parameters. These parameters are used to test their trend. The segment of signal may be called y_i . These parameters are tested in this method are as mentioned in a previous section which represents TD parameters. Next, to test the sequence of numbers y_i associated with each parameter for variations outside, the expected value due to sample variations is done by calculating a new function h_{ij} , as [19]

$$h_{ij} = \begin{cases} 1 & \text{if } y_i > y_j \text{ for } j > i \\ 0 & \text{otherwise} \end{cases} \dots \dots (11)$$

Where $i = 1, 2, \dots, N-1$, and $j = i+1, i+2, \dots, N$.

Calculating A_i factor for each number as:

$$A_i = \sum_{j=i+1}^N h_{ij} \dots \dots (12)$$

The variable A number of reverse arrangements can be estimated by:

$$A = \sum_{i=1}^{N-1} A_i \dots \dots (13).$$

The mean and variance of a N set of independent observations of a stationary random variable are given by the two respectively equations[20], [6]:

$$\mu_A = \frac{N(N-1)}{4} \dots \dots (14)$$

$$\text{var}_A = \frac{N(2N+5)(N-1)}{72} \dots \dots (15)$$

$$Z = \frac{A - \mu_A}{\sqrt{\text{var}_A}} \dots \dots (16)$$

Under the null hypothesis of this test the data points in the signal are shown independent observation from random variables [10]. The alternative or renewal hypothesis however showed that the data points that make up the signal are related and there is an underlying trend in a sequence of observations. The hypothesis of stationary are accepted at the $\alpha = 0.05$ level of significance if A is in the range [19]:

$$A_{N;1-\alpha/2} < A \leq A_{N;\frac{\alpha}{2}} \dots \dots (17)$$

If the observed runs fall outside the interval, the hypothesis is rejected at α level of significance.

4. Artificial Neural Network

ANNs attempt to emulate their biological counterparts. ANNs have been developed in the form of parallel distributed network models based on biological learning process of the human brain [12]. There are different methods used to deal data in ANN application. Between different types of Artificial Neural Networks, multilayer receptors (MLP) neural networks are common to a reasonable extent and used for this work. The classical three layers feed forward NN architecture is shown in fig. 1.

Fig. 1 three layer NN structure

For a network with N input nodes, H hidden nodes and M output nodes, the mapping from input vector $(I_1, \dots, I_N)$ to the output vector $(O_1, \dots, O_M)$ is given by:

$$O_q = g\left(\sum_{j=1}^H V_{jq} h_j\right) \dots \dots 18$$

Where $q=1, \dots, M$, V_{jq} is the weight from hidden node (j) to the output node (q) and (g) is the activation function. The value of hidden layer node h_j is given by:

$$h_{qj} = \sigma\left(\sum_{i=1}^N w_{ji} + b_j\right) \dots \dots 19$$

Where w_{ij} is the input weight, b_j is the threshold weight and σ is the activation function which is in this work chosen as the sigmoid function which is very popular because it is monotonous, bounded and has simple derivative. The general back propagation training takes place in three stages, firstly; feed forward of the input training pattern, secondly; back propagation of the associated error, and finally; weight adjustment.

The sigmoid activation function is popular for neural network applications. Since it is differentiable and monotonic, both of which are a requirement for the back-propagation algorithm. The equation for a sigmoid function is [21]:

$$J(s) = \frac{1}{1 + e^{-s_i}} \dots \dots 20$$

Where s_i is the weighted sum.

5. Fault Detection Architecture

The flow chart of fig. 2 shows the proposed method. It is based on fusion of data of multi-sensors. The signals are taken from MFS under two conditions. First, is normal operation condition; second is faulty state of machine. These data is transferred through data acquisition system. TD features are extracted from the measured signal from four sensors. These sensors are mounted in four different locations (vertical and horizontal inboard, and vertical and horizontal outboard). Then, the trend associated with each fault for the features extracted from the four sensors are check by RAT. The feature has influence with any fault is marked by best feature, while the feature has not any influence in fault change this feature is marked as rejected feature. The best features are used as input to ANN to accomplish the training of network. After training method the features are classified with each fault types. Then, the test of the features, and their ability to identify fault are examined. This method is used to fault detection. The features are different in their affect with each types of fault, so that all features of TD domain should examine to identify the best features associated with each individually fault.

Fig. 2 Flow Chart of Proposed Method

6. Experimental Work

To verify the proposed method the Machinery Fault Simulator (MFS) is used fig. 3. The bearing faults are studied. These faults are outer race inner race and ball and bearing wear. The MFS will be configured to collect first on good quality inboard and outboard rotor bearings. It is essential that the machine be properly aligned. Defective bearing will be introduced one at a time and data collected. The objective is to compare the results of good bearings to defective bearings. The data are collected at 10 KHz frequency range. The speed of machine rotation is 2700 RPM.

Fig. 3 MFS photography

7. Results and Discussion

A. RAT

The best features needed to clarify the different bearing faults are done. The most important effective features on the fault are chosen according to take a set of data at rotational speed of 2700 RPM. Time domain features are estimated for a ten reading parts for each rotational speed in the four directions (vertical Inboard VI, horizontal inboard HI, vertical outboard VO, and horizontal outboard HO). The sample rate is 4096 sample/sec, where the number of sample is 40960 sample/reading. The RAT of these data is calculated as illustrated in table 1. The acceptance values of RAT indicator as AC while the unacceptance by UA. The results that have been obtained from RAT for time domain Factors showed these which are not mostly fit to be an indicator of ball bearing fault. So it is better to look for another way to get a good indicator of this fault. But would like to point out here that Kurtosis, shape, Skewness still an influence in fault detection, these features were giving indicators for condition prognosis and fault diagnosis. Also the More effective directions in the identifying ball fault are the horizontal and vertical Ranked by priority. In vertical direction the features that are more effective in identifying the inner race fault were Kurt, shape factor, and Skewness, while in horizontal direction these features are kurtosis, Skewness, impulsive, and crest factors. These features are estimated in outboard or on the cage of faulted bearing while inboard cage still as a reference to vibration signal as showed in table 2. Here we showed that these features will be the inputs of intelligent system. To identify outer race fault by using RAT method, table 3 showed that the

features are Kurt, shape factor, impulsive, and skewness in both vertical and horizontal directions, except that in the horizontal direction has further feature it is crest factor, so that the horizontal direction regarded as the best direction that could be used in this fault identification. As shown from the observation of the three tables of each individual bearing fault, that there is ability to infer the compound fault table of RAT, but according to the readings of vibration data associated with compound fault the RAT of it as shown in table 4, the dominated direction used to identify compounds bearing fault was horizontal, upon this the feature associated with this direction were RMS, Standard deviation, Kurt, shape, impulsive, clearance, and crest factors, also the shape factor in vertical direction should be checked in intelligent system to increase the viability of detection faults. From the study of the bearing faults one can conclude that the effect of the fault on one support inboard and outboard, and that clearly from the tables. The effect of a bearing fault didn't extend from one support to another support and study localized defect. This fact will be benefit in fault diagnosis.

Table 1 RAT in TD Factor for Ball fault VI

	VO		HO		VI		HI	
Mean	7	UA	5	UA	8	UA	9	UA
RMS	8	UA	9	UA	9	UA	10	UA
SD	8	UA	9	UA	9	UA	10	UA
Kurt	20	AC	30	AC	42	UA	36	UA
Shap	20	AC	30	AC	44	UA	31	AC
Implsf	24	AC	31	AC	42	UA	41	UA
Clearcf	40	UA	41	UA	41	UA	40	UA
Crestf	25	AC	31	AC	42	UA	41	UA
Sk	10	UA	26	AC	34	AC	28	AC
Peak	11	UA	10	UA	10	UA	9	UA

Table 2 RAT for Inner Race Fault in TD

	VO		HO		VI		HI	
Mean	3	UA	6	UA	11	UA	15	AC
RMS	7	UA	6	UA	7	UA	7	UA
SD	7	UA	6	UA	7	UA	7	UA
Kurt	31	AC	24	AC	44	UA	38	UA
Shap	22	AC	22	AC	41	UA	34	UA
Implsf	37	UA	21	AC	40	UA	39	UA
Clearcf	39	UA	38	UA	40	UA	37	UA
Crestf	36	UA	22	AC	40	UA	39	UA
Sk	33	AC	36	UA	26	AC	26	AC
Peak	9	UA	4	UA	6	UA	8	UA

Table 3 RAT for Outer Race Fault in TD

	VO		HO		VI		HI	
Mean	4	UA	3	UA	11	UA	22	AC
RMS	9	UA	8	UA	5	UA	6	UA

SD	9	UA	8	UA	5	UA	6	UA
Kurt	29	AC	26	AC	42	UA	37	UA
Shap	28	AC	19	AC	42	UA	33	UA
Implsf	33	AC	31	AC	37	UA	38	UA
Clearcf	39	UA	38	UA	39	UA	39	UA
Crestf	36	UA	32	AC	37	UA	38	UA
Sk	14	AC	23	AC	19	AC	43	UA
Peak	11	UA	9	UA	8	UA	7	UA

Table 4 RAT for Compound Fault in TD

	VO		HO		VI		HI	
Mean	7	UA	2	UA	9	UA	3	UA
RMS	9	UA	19	AC	11	UA	10	UA
SD	9	UA	19	AC	11	UA	10	UA
Kurt	35	UA	19	AC	42	UA	41	UA
Shap	29	AC	13	AC	41	UA	33	AC
Implsf	39	UA	22	AC	41	UA	40	UA
Clearcf	40	UA	23	AC	39	UA	40	UA
Crestf	39	UA	23	AC	40	UA	40	UA
Sk	39	UA	38	UA	19	AC	22	AC
Peak	7	UA	8	UA	11	UA	8	UA

B. ANN

In this method the traditional a three layers NN are used; the features extracted from time domains are used as input node in the input layer. One node in the output layer their value set to be zero when the data referred to normal operation condition (NOC) while the output value set to be one which referred to the faulty operation case (FOC). The main program used to calculate the NN weights, are written in visual basic. The mean square error of training method is dropped under using different number of node in the hidden layer (NHN) which is start in training from 10 NHN to 23 NHN, the best NN architecture is [20- 20-1] as shown in table 5. The reason to use all the features extracted from the time domain is the fact that these features associated in a different way with different kinds of faults. In the fault detection process cannot speculate on a specific type of faults so that we can use those features that have been previously identified and related to various failures. So, in fault detection process requires used collectively in order to be reached disclosure faults for different types from a wide range of data that may contain a certain type of faults. Despite the fact that the neural network training capacity might at best do not exceed 95%, but it's good to detect the state of rotating machine. For validation, the NN method for fault diagnosis used either with NOC and FOC as shown in table 6 as their values can be estimated with FOC using different cases under test their prediction accuracy against the number of node in the hidden layer. Fig. 4a part of the

training program and the test case shows the machine under test in the case of normal working. The other Fig. 3b is for the case where the machine malfunctions. This part of the program is installed during the training process and tests various data and is part of the training and not the final program, which will be used later for the purpose of detection and prediction of the type of fault in rotary machines. This is a part of the testing process of the program with the possibility of detecting faults and for the purpose of installing possibility available to it, also makes sure that it will work in the detection process. The possibility of detecting various faults using this part of the program is shown good results and obtained are 100% for different types of faults. The value of error is estimated as [3]:

$$\%error = \frac{[act. value - est. value]}{act. value} \times 100 \dots 21$$

Table 5 Training of NN

NHN	Estimated value	Actual value	Time Consumption (sec)	Total No. of Training
10	0.8164	1	12.73	800
15	0.7894	1	15.04	800
17	0.8039	1	15.04	800
20	0.9527	1	19.67	800
21	0.9425	1	20.83	800
23	0.9266	1	20.83	800

Table 6 Diagnosis of different cases Using NN

NHN	Estimated Value	Actual Value	Percentage Error %
10	0.1882	0	18.82
15	0.0952	0	9.52
17	0.0661	0	6.61
20	0.0565	0	5.65
21	0.0511	0	5.11
23	0.1015	0	10.15

(a) Normal Operation Case

(b) Faulty Machine State

Fig.4 Machine Operation condition

B.1 Training Error versus Epochs

When the number of cases is increased and become greater than four cases between NOC and FOC, the error estimated against numbers of epoch is showing some fluctuating in their values, but in general the degradation trend towards to approach zero, it was shown the tendency to be minimized to the smallest value fig.5, and fig. 6 explain these facts, also from the increasing number of epochs shows getting smallest values.

Fig.5 Error against the epochs for 100 iteration and 4 cases

Fig.6 Error against the epochs for 800 iteration and 8 cases

B.2 Comparison Actual Value and ANN

The prediction method using neural network operation is showed a distinctive performer as the overall fault prognosis method. The difference between the neural network and the actual values is very little and this indicates a good use of neural network in distinguishes faults fig. 7 showed the data degradation trend of bearing until a serious operation index for this type of bearing from the desirable operation state. These data is recorded in duration from 29/10 to 30/11 where the type of bearing is under revolution speed of 2700RPM, the loading condition is applied by screw tightening until serious state reached according to ISO 10816-3 Vibration Severity Chart.

Fig.7 Comparison Actual value and ANN

8. Conclusions

In this work, we attempt to use a novel method to detect the trend in features used in the bearing fault detection process. RAT method has been effective in the extraction well and the necessary features associated with each failure independently and given sufficient accuracy in distinguishing different types of defects. The TD features are chosen in order to identify the different types of faults in rotating machine. The RAT is used to verify the trend in data of these features so as to detect the relationship between features and each fault. RAT method has shown that these data are within the scope for the detection of faults, because of the existence of the trend in the data associated with each fault. It has been identified the degradation of the machine. RAT is found that not all types of fault have the same identification features. In other word, for each fault there are

certain types of features as shown in all tables. ANN regarded as best and important an effective method to fault detection process. ANN give a detection results of 100% about statement of machine operation condition either it is worked normally or faulty.

Availability of data and materials

Data can be provided you.

Declaration of competing interest

The authors declare that they have no known competing for financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT authorship contribution statement

Mohammed AL-SAAD Conceptualization, Methodology, Writing - original draft, Software, Validation, Formal analysis. Mohammed Al-Mosallam: Conceptualization, Supervision, Investigation, Project administration. Ahmed A. M. Alsahlani: Software, Investigation, Writing -review & editing.

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