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Study of Intelligent Diagnosis in Machines

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ABSTRACT: Intelligent fault diagnosis is emerging as an important phase in achieving an acceptable and competitive cost and reduction in human labor. In this paper, the research and development of new algorithms and methods have been discussed which help in automating the fault diagnosis of machines. The major emphasis is to study the fault detection using approaches like neural networks, industrial wireless sensor networks, empirical mode decomposition and so on. Applications of this would be used in industries, motor bearings, rotating machinery, wind turbines.

KEYWORDS: Intelligent fault diagnosis, neural networks, vibration signals, mechanical big data, feature extraction, mechanical fault, rotating machinery.

I. INTRODUCTION

In modern times, industries and machines have become more efficient thus increasing the significance of monitoring their health conditions. To fully inspect the health conditions of the machines, condition monitoring systems are used[11]. A huge amount of real-time mechanical big data is collected using sensors[12]. The vibrations are generally collected faster in comparison with the analyzing process of the data collected. This makes intelligent fault diagnosis a very important topic for research in recent times. Intelligent fault diagnosis provides more accurate and precise results for a large amount of data produced hence making it an efficient tool for managing mechanical big data. In order to check the health status of a machine, first the input signals are collected. These input signals can be vibrations or sound signals[13]. The necessary features are extracted from these signals using various algorithms. These extracted features are then used for condition monitoring and fault diagnosis. The following diagram shows the generalized approach for the fault diagnosis of the machinery.

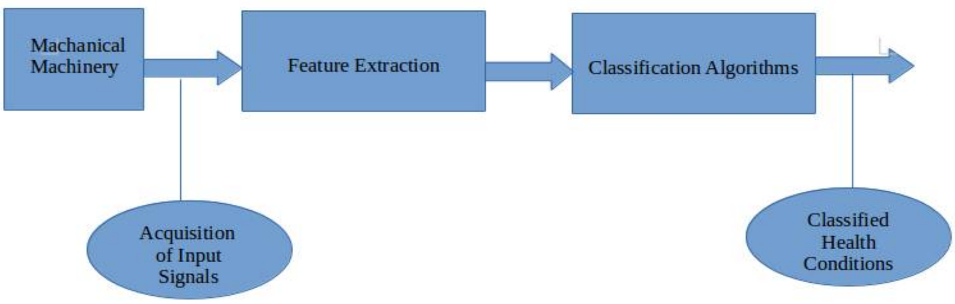

Figure 1. Generalized mechanical fault diagnosis process

The chapter 1 of this paper gives an introduction of the topic and the methods used in short. Chapter 2 gives the classification of various methodologies. Chapter 3 illustrates the existing approaches towards handling mechanical big data and diagnosing mechanicals faults, Chapter 4 gives the comparative analysis in a tabular form. Chapter 5 gives the summary and chapter 6 includes the references.

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II.CLASSIFICATION

Recently various techniques for fault diagnosis have been proposed. These approaches differ in their aspects of implementations. Obtaining inputs, feature learning and faults classification of these approaches further lead to their classification as follows:

Classification based on inputs

i. Vibration signals inputs : In these approaches, the vibrations of the machines are converted into vibrating signals in order to learn the features for fault determination
ii. Sound signals as inputs : The sound signals are obtained by placing the microphone near the rotating machinery.
iii. Images as input : Images can be used as inputs for fault classification either by thermal images obtained from thermal cameras or by simple images.

III. EXISTING TECHNIQUES

In [1],Yuan Xie et al. presented an innovative approach to extract the distinguish characters from a nonstationary vibration signals. Empirical Mode Decomposition (EMD) and Convolutional Neural Networks(CNN) were used for feature elicitation while Support Vector Machine(SVM) and softmax classifier are applied for the classification of the health status. At the beginning, the vibration signals of a spinning machinery is disintegrated to a set of intrinsic mode functions (IMFs). The EMD and CNN techniques are used for extraction the features from these signals by implementing the statistical time domain features as fault features, including mean, skewness, ,standard deviation , kurtosis and root mean square.Next, SVM and softmaxclassifier are used for the classification of the health conditions of the rotating machinery. The approach considers length, strides and the filter numbers as the parameters. It is a self adaptive processing method and hence very less manual interference is required. Inner race faults, the ball of rolling bearing faults, and the outer race faults are the health conditions classified by this approach. The fault diagnosis rate for this specific method is near about 99%.

In [2], Faisal Al Thobiani et al, proposed a fault diagnosis approach for rotating machinery utilizing thermal imaging and ARTMAP. Thermal imaging provides the ability to display the distribution of the temperature and indicates the operating conditions of the machines by its temperature. The approach implements minimum redundancy maximum relevance (mRMR) for feature selection and extraction while simplified fuzzy ARTMAP (SFAM) for classification of the faults of the rotating machinery. Initially the thermal images are captured with the help of the thermal camera which is the key acquisition device. The thermo-grams are processed for improving the quality of he image by removal of noise, cropping in accordance to the region of interests and adjusting the contrasting levels. The statistical characteristics of thermo-gram are used for feature selection along with the Redundancy Maximum Relevance (mRMR). mRMR is a feature selection technique generally used in methods for accurately determining the characteristics.BEMD-PCA combinations are used for image enhancement prior the extraction of the features from gray-level concurrence matrix(GLCM). This stage produces a high dimensionality of features. Later the simplified fuzzy ARTMAP : an incremental neural networks are implemented for the classification of the health conditions of the rotating machinery. SFAMF are used for fast training and online or offline learning. The health condiions like Normal,misalignment, mass unbalance and faulty bearing conditions could be classified by the use of this approach.This approach can result in accuracy of 100% for three and more selected features.

In [3], Chuan Li et al. proposed an approach for classification of faults using the acoustic and vibration signals as inputs. The method was designed for gearboxes. Gearbox failures may cause issues like increased repair costs, undesirable halts, etc. To enhance the classification performance, Deep Random Forest Fusion(DRFF) was applied in the method. Acoustic Emission(AE) sensors along with an accelerometer were employed for observing the health status. Initially, using input AE and vibration signals wavelet packet transform parameter are generated. Afterwards, for the deep representation of parameters deep Boltzmann machines(DBMs) are generated. Finally, a random forest is suggested to combine the outputs of DBMs to form integrated DRFF (Deep Random Forest Fusion) model. The health

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conditions like bearing ball fault, outer race faults and eccentric bearing house were classified in this particular method which further resulted in the classification rate of 97.68%.

In [4], Yaguo Lei et al. proposes a novel approach for fault diagnosis of machinery using the intelligent extraction methods rather than traditional manual feature extraction approaches. This approach uses sparse filtering for feature extraction and softmax regression for the classification of health conditions. The locomotive bearing and motor bearing are the machinaries being used. It was a adaptive learning method and hence required minimal human tasks. Initially, sparse filtering, a unsupervised algorithm was implemented for feature extraction. Sparse filtering is a two layered neural network which optimized the distribution of the characteristics. In the next step, softmax regression is used to classify the health conditions of the machinery. A process known as whitening was also implemented in order to reduce the noise errors if any during the fault diagnosis. Considering the locomotive bearings there were seven health conditions classified as normal condition, slight rub fault in outer race, serious flaking fault in outer race, slight rub fault in inner race, roller rub fault, concurrent faults in outer race and roller and concurrent faults in the inner race and roller. The accuracy for the locomotive bearing using this approach was about 99%. While there were four health classified in the motor bearing like normal condition, inner race fault, outer race fault, and roller fault. The accuracy for the motor bearing using this approach was near about 99.66%.

In [5], unlike traditional analysis methods, image-processing based fault diagnosis method is presented. Health condition of rotating machinery is imperative for the reliable operation of the system. Chen Lu et al. proposed this method which avoids the drawbacks of relying on a diagnostician for feature extraction in traditional approaches. At first, the bi-spectrum contour map is used for the transformation of vibration signals to images. The intermediate step for this transformation includes the conversion of vibration signals to bi-spectrum contour map and SURF (speeded up robust features) is employed to extract the features from this contour map. Furthermore, t-SNE (Stochastic Neighbor Embedding) is utilized to reduce the dimensionality of the SURF feature vectors. For every detected feature point SURF generates a 64-dimensional feature vector which may result in feature redundancy and resource wastage therefore, dimension reduction is required. Finally, probabilistic neural network is introduced for fault identification. For the verification of approach axial piston hydraulic pump and self-priming centrifugal pump are used and the average accuracy of the experiment is above 97%.

In [6], M. Saimurugan et al have used sound signals for fault diagnosis. These sound signals are obtained by placing a microphone near the bearing which is to be diagnosed. The sound of the bearing for various speeds is obtained.Using sound signals for fault diagnosis is cost effective than using vibration signals. In this approach the feature extraction is done by using histogram and statistical methods like mean, median, standard deviation, etc. as these signals are of random type and using these methods results in simple and quick computations. Spectral segmentation process is used for fusion of signal.In spectral segmentation process the frequency spectrum of signals is partitioned into fine segments and thereafter based on different subsets these segments are merged. This approach makes use of decision tree algorithm and artificial neural networks for feature extraction and classification.The finest features of the sound signals can be acquired using the decision tree algorithm Artificial Neural Network classifies the faults/health conditions of the bearing. The extracted features are the input of artificial neural networks.This model functions by collecting signals from 'n' distinct sources.The output signal function is generated by subsequent transformation. The accuracy of matrix is found to be 94.5% by using this approach.

In [7], Chia Wang et al. have proposed a approach to diagnose shaft fault types. As the vibrating signals emitted by faulty shafts are non-stationary and non-linear, its diagnosis is restricted by the limitations of linear analysis which makes it difficult to accurately evaluate the working condition of the shafts. Initially, based on vibration signal the shaft faults extraction is performed using MSE, EMD and Fourier transform. The disintegration of the signals into multiple Intrinsic Mode Functions (IMFs) is done using EMD algorithm. The patterns in both EMD and MSE curves are used to differentiate the shafts with different conditions. Shafts having conditions as insufficient grease, excessive grease, insufficient preloading, excessive preloading, and bearing damage were called as abnormal and successfully detected by the system. Finally,423 shafts were analyzed by using this approach and the accuracy of the outcome was above 60%.

In [8], Linfeng Deng and Rongzhen Zhao have proposed a fault diagnosis approach based on pattern recognition. According to the authors, any general fault diagnosis approach comprises of three main stages as data acquisition, feature extraction and selection, condition identification. In this approach, LMD(local mean

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decomposition) algorithm is applied to decompose the input vibrating signal; then for deriving the principal features KPCA i.e kernel principal component analysis is performed and lastly condition identification is done by least squares support vector machine. The experiment mainly deals with four types of machine faults namely, Shaft misalignment, loose bearing, rotor stator rubbing, rotor mass imbalance. The accuracy of the experiment is directly proportional to the number of PCs i.e principal components analyzed. These PCs are extracted from the fault features. The minimum accuracy (two PCs) for the method is 95.42%. When 10 PCs are used the accuracy is nearly 100%

In [9], LiqunHou et al. Proposed a novel approach for monitoring machine conditions using the industrial wireless sensor network. In this two stage approach: on sensor feature extraction , neural networks for classification are used along with the Dempster-Shafer theory for increasing the quality of results in fault diagnosis. The approach was implemented on the motor stator. The vibration signals are measured using the ADXL335 micro-electromechanical systems (MEMS) accelerometer. In the first stage, the feature extraction is done using peak-to-peak amplitude and variance values present in the time domain. On-sensor feature extraction decreases the amount of transmitted data and thus saves the energy of the node improving the node lifetime. Later, backpropagation neural networks are implemented for the classification of the health conditions on the nodes of the sensor. In the Dempster-Shafer mathematical theory the eclectic information from various distinct sources are combined to obtain the proposition intersection and the probability associated with these data. The approach classifies four major health conditions such as normal without load, normal with load, loose feet and mass imbalance. The accuracy of this approach was at least 97.5% for the fault diagnosis of the motor stator.

In [10], SmailBachir et al have proposed a new model dedicated to squirrel-cage induction machines has been presented for the realistic identification and detection of stator and rotor faults. First, the interturn short-circuit winding have been modeled by a short-circuit element. Each element has been dedicated to a stator phase in order to explain the fault. Second, a new equivalent Park's rotor resistance has been expressed to allow the decreasing of the number of rotor bars in faulty situation. Parameter estimation is used to perform fault detection and localization. Two parameters each have been considered for both stator as well as rotor models. The parameters introduced to define the stator faults. 1) The localization parameter θcc, which is a real angle between the short-circuitinterturn stator winding and the first stator-phase axis (phasea).This parameter allows the localization of the faulty winding. 2) The detection parameter ηcc equal to the ratio between the number of interturn short-circuit windings and the total number of interturns in one healthy phase. Parameters introduced to ex- plain rotor faults. 1) The angle $\theta 0$ between fault axis (broken rotor bar axis) and the first rotor phase. This parameter allows the localization of the broken rotor bar. 2) To quantify the rotor fault, a parameter $\eta 0$ was introduced equal to the ratio between the number of equivalent interturns in defect and the total number of interturns in one healthy phase. Experimental tests illustrate the efficiency of this technique for use in offline stator and rotor faults diagnosis of induction machine under varying speed. The estimates of the number of interturns short-circuit windings and broken rotor bars in different realizations give a good approximation of the fault level in the machine.

IV.COMPARATIVE ANALYSIS

Sr No	Algorithms	Datasets	Health Conditions	Accuracy
1	Compound Quadratic Criterion and Minimization of the Compound Criterion	Rotor and stator	Healthy motor, good absorption of spectral lines, optimum criterion is high.	Good approximation
2	Dempster–Shafer Theory, backpropagation neural networks, on sensor feature extraction.	Motor stator current and vibration signals	normal without load, normal with load, loose feet and mass imbalance	98%
3	SURF, bi-spectrum contour map,probabilistic neural networks	Rotating Machinery	bearing roller wearing, inner race wearing, outer race wearing, and normal conditions	97%

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4	Empirical Mode Decomposition, Multi-scale Entropy	Rotating Shaft	insufficient grease, excessive grease, insufficient preloading, excessive preloading, and bearing damage	Above 60%
5	Decision Tree, Artificial Neural Networks	Rotating Machinery	Good Shaft with Good bearing , Unbalanced Shaft with Good bearing , Good Shaft with Outer Race Fault in bearing (ORFB) , Unbalanced Shaft with Outer Race Fault in bearing (ORFB), Good Shaft with Inner Race Fault in bearing (IRFB),Unbalanced Shaft with Inner Race Fault in bearing (IRFB)	94.5%
6	Empirical mode decomposition,Convolutional Neural Networks, Support Vector Machine, Softmax regression	Rotating Machinery	Inner race (IR) fault, outer race (OR) fault, ball of rolling bearing(BA) fault.	Around 99%
7	Sparse Filtering, Softmax regression.	Locomotive bearing, motor bearing	normal condition, slight rub fault in outer race, serious flaking fault in outer race, slight rub fault in inner race, roller rub fault, concurrent faults in outer race and roller and concurrent faults in the inner race and roller(locomotive bearing), like normal condition, inner race fault, outer race fault, and roller fault(motor bearing).	Around 99.66%
10	local mean decomposition, kernel principal component analysis, least squares support vector machine	A Rotor-bearing	Shaft misalignmenr, loose bearing, rotor stator rubbing, rotor mass imbalance	Above 95
11	Redundancy Maximum Relevance(mRMR), simplified fuzzy ARTMAP	Rotating Machinery	Normal, misalignment, faulty bearing, mass unbalance	Above 85 (100 for 3+ features)

V.SUMMARY

We have studied various Intelligent fault diagnosis approaches with their performance evaluation, datasets and other characteristics. These approaches can be used in various fault detection purposes according to convenience. Contrastive survey of different approaches help in understanding the implementation in a better way. Moreover we have also seen the widely used data sets for age estimation along with their features.

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