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Comparison of CWRU dataset-based diagnosis approaches: review of best approaches and results

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Abstract. Bearings are the most common mechanical components in machines. Once a bearing fails (or components in it), other adjacent components or the machine itself are effected up to failure. Therefore, bearing health condition is of great interest in practice. Several benchmark datasets are developed to evaluate development in bearings health state (diagnosis) and remaining useful lifetime (prognosis). Among these datasets, Case Western Reserve University (CWRU) dataset is one of the most cited ones used to validate the performance of different diagnostic approaches. Over recent years, a significant amount of research approaches are developed using CWRU data. Most approaches are focused on specific performance parameters like detection rate or accuracy etc. The main problems in connection with CWRU dataset use are: no overview about latest results is available. Furthermore several results published are not complete, for example published accuracies rate without false alarm rates.
In this contribution an overview about the development change over the last years, the approaches applied, and specifically the results obtained will be given. Additionally, the new approaches emerging in recent years like deep learning (DL) also in combination with fusion methods and related performance will be given in comparison with conventional machine learning (ML) methods. Special care will be given to the completeness of published results also in combination with shown robustness. As outcome of this contribution the newest and best results are noted, furthermore a recommendation how to complete research work using benchmark dataset will be given. Although most approaches using CWRU dataset as benchmark get high accuracy. For further bearing fault diagnosis research, more and more suitable measures as well as other datasets are needed for increased performance evaluation.

Keywords: Bearing dataset, CWRU, diagnosis, deep learning, machine learning, performance, review

1 Introduction

Within the last decades, rotating machinery equipment plays an irreplaceable role in modern industry [1]. As one of the most common components of rotary machinery, bearing is a mechanical component used to reduce friction among other moving parts. Once a bearing fails (or components in it), other adjacent components and machines are effected up to failure. Several surveys regarding the likelihood of induction machine failure conducted by the IEEE Industry Application Society (IEEE-IAS) and the Japan Electrical Manufactures' Association (JEMA) reveal that bearing fault is the most common fault type and is responding for 30 to 40 % of all machine failures [2]. Therefore, condition monitoring and fault diagnosis of bearings is of increasing interest [3]. Several benchmark datasets are developed to evaluate development in bearings health state (diagnosis) and remaining useful lifetime (prognosis). Among these datasets, Case Western Reserve University (CWRU) dataset is one of the most cited ones used to validate the performance of different approaches on bearing diagnosis. In general, there are three kinds of bearing fault diagnosis methods: signal-based methods, model-based methods, and data-driven methods. Due to the development of smart manufacturing and the widely application of intelligent sensors, the data-driven fault diagnosis methods have attracted many studies in recent years [4]. Machine learning (ML), deep learning (DL), and transfer learning (TL) are powerful data-driven methods.

Many approaches applying to bearing fault diagnosis have been proposed in the last years, however, there is no common standard to judge the performance of these approaches. Usually, several options are known to evaluate the outcome of algorithms and the classifiers: accuracy, precision, recall (sensitivity), specificity, F-score and receiver operating characteristic (ROC). Every metric has its pros and cons: accuracy assess the overall effectiveness of algorithms, precision assesses the predictive power of algorithms, sensitivity and specificity access the effectiveness of the algorithm on a single class; F-score benefits algorithms with higher sensitivity and challenges algorithms with higher specificity; ROC shows a relation between sensitivity and specificity of algorithms [5]. At present, accuracy has been widely used as the metric to evaluate the fault diagnosis approaches. However, fault diagnosis is by definition an imbalanced classification problem where the positive class (machine faults) is greatly outnumbered by the negative class. The accuracy metric is therefore not an appropriate measure for assessing model performance—a classifier with a focus on merely getting the negative instances correct will have a high accuracy by definition, but it will not be useful for identifying the few positive instances (i.e. machines faults) when it really matters [6]. Therefore, more metrics should be included in the results of algorithms.

The structure of this paper is organized as follows. A brief introduction of CWRU bearing dataset is given in section 2. In section 3, the approaches applying for CWRU dataset are summarized. Results and resulting challenges of these approaches are presented in section 4. Suggestion for fault diagnosis and conclusions are given in section 5.

2 Case Western Reserve University bearing dataset

Collected by Prof. Kenneth Loparo's research group at Case Western Reserve University, CWRU dataset provides access to ball bearing test for normal and faulty bearings.

As shown in Figure 1, the test stand consists of a 2 hp motor (left), a torque transducer/encoder (center), a dynamometer (right), and control electronics. Motor bearings were seeded with faults using electro-discharge machining (EMD). Faulted bearing were reinstalled into the test motor and vibration data was recorded for different motor loads (labeled as 0, 1, 2, 3) horsepower (motor speeds of 1797 to 1720 rpm). Faults ranging from 7 mils in diameter to 40 mils (1 mil = 0.0001 inch) in diameter were introduced separately at the inner raceway, ball, and outer raceway. As the placement of outer raceway faults is relative to the load zone of the bearing and has a direct influence on the vibration signal, therefore, the position of outer raceway faults was located at 3 o'clock (directly in the load zone), at 6 o'clock (orthogonal to the load zone), and at 12 o'clock [7].

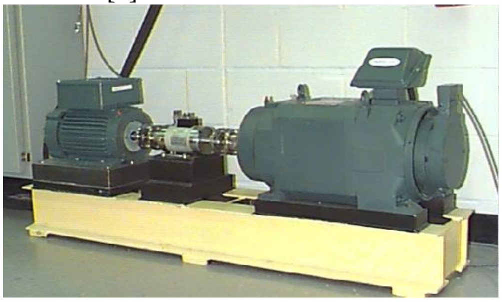

Fig. 1. Test rig used in the Case Western Reserve University Lab [7].

Vibration data was collected using accelerometers, which were placed at the 12 o'clock position both the drive end and fan end of the motor housing. For drive end bearing faults, data was collected at 12,000 samples/second and 48,000 samples/second. All fan end bearing data was collected at 12,000 samples/second [7].

3 Approaches used for CWRU bearing dataset

Data-driven fault diagnosis can be divided into three types: machine learning-based, deep learning-based, and transfer learning-based. In this section, approaches applying for CWRU bearing dataset would be summarized.

3.1 Machine learning approaches

Machine learning algorithms which remove manual observation or interpretation on model-based approaches is one of the main methods to handle the data in fault diagnosis [8]. Many researchers have applied machine learning algorithms to fault diagnosis, including: support vector machines (SVM), artificial neural networks (ANNs), expert system, fuzzy logic (FL), principle component analysis (PCA), and K-Nearest Neighbors (k-NN) [2]. Comparing with other machine learning approaches, SVM-based approaches [9]-[19] are used most in the last 5 years when detailed to CWRU bearing dataset.

3.2 Deep learning approaches

According to [20] deep learning approaches have the potential to overcome the inherent shortcomings of the traditional intelligent diagnosis methods. The most success of deep learning methods is the ability to automatically learn the representative features from raw data [21]. Deep belief network (DBN), convolutional neural network (CNN), auto-encoder (AE), recurrent neural network (RNN) and generative adversarial network (GAN) are popular deep learning methods for fault diagnosis. Many approaches based on DBN [22]-[26] use the CWRU bearing dataset as input. Fault diagnosis methods applying to CWRU dataset based on CNN are presented in [27]-[31]. Auto-encoder based papers [32]-[39] also illustrate the effectiveness and efficiency of employing auto-encoder to serve for fault diagnosis. Besides, other deep learning algorithms are also applied on CWRU bearing dataset, such as: low-delay lightweight recurrent neural network (LLRNN) [40] and multi-manifold spectral clustering based on particle swarm optimization (MMSC-PSO) [41].

3.3 Transfer learning approaches

Transfer learning (TL) performs learning on training datasets (called source problem) and then to perform the same task on the test dataset (called target problem) from a related distribution. Compared with shallow structures, TL offers greater flexibility in extracting high-level features transferred from the source to the target problem [33]. Contributions [6], [33], [42] prove that TL is a powerful algorithm.

4 Results and resulting challenges

A systematic comparison of the different algorithms and related results employing the CWRU bearing dataset is presented in table 1. From table 1, the following conclusions could be drawn:

1. Approaches differ with respect to feature extraction algorithms and classifier. To calculate dataset effectively, researchers design various structures and combine multifarious algorithms. Namely, most of these approaches are novel and unique so the CWRU dataset only serves as application example.
2. Most of the contributions select individual data combinations from CWRU dataset: different work conditions, fault sizes, training/test samples ratios. In [12], [13], [30], [6], [33], as the training/test ration is variant, the detection accuracy shifts. Besides, some contribution select the data from CWRU dataset to build up their own dataset, in [15], [19], [29], [6], [33], [41-42], different dataset are build. The difference of selecting data affects the test accuracy.
3. Most of approaches could reach high detection accuracy. Especially in [19], [24] detection accuracy could reach 100 %. However, most approaches with high accuracy are applied on a specific sub-dataset with fixed operating conditions.
4. Most of these approaches use detection accuracy as metrics. Few approaches use other standards to judge the performance of these approaches. Only [10], [13], [14],

[6], [34] apply precision, specificity, recall, F-score, PPV, and ROC curve as approach's metrics.
5. Although there are many methods for bearing fault detection, there are few methods used for predicting fault size, only in [9], [16], [17] the fault severity is calculated.

5 Recommendation and conclusions

At present no standard metrics is applied to judge the overall performance of algorithms, however, from table 1, the following conclusions could be drawn:
1. Different operating conditions and different fault sizes data are chosen in [9], [14], [16-17], [22], [25-29], [31], [6], [33], [39], [42], therefore, the robustness of these algorithms is higher than those of others. Approaches [26], [6], [17], [28], [33], [42], [9], are trained on one load, but tested on other loads. Additionally, in [9] the approach is also trained on another fault size. In this sense, [9] choses broader data as input.
2. The perfect solution to deal with the illustrated complexity is to use N-fold cross validation. N-fold cross validation is applied in [9], [10-11], [13-14], [17], [30], [34], [38-39], [40], [42]. Especially, in [14], other metrics besides accuracy are calculated. Due to the results achieved this approach appears as the actual best approach applied to CWRU dataset.
3. To verify the performance of algorithms, some contributions apply their algorithm to other dataset, [10], [12], [22], [25-28], [31], [6], [38], [40]. Therefore, the results of these algorithms applying to other dataset should be considered in evaluating the performance of these algorithms.

From the analysis of the existing results (table 1) some formal conclusions can be drawn:
1. Results are dataset- and metric-specific, so they can not be compared really.
2. Results are often only shown as accuracy, so they are not representative for unbalanced datasets.
3. Results are often only applied to CWRU dataset, so their applicability to other benchmark data sets can not be concluded.
Some further statements can be concluded:
The performance of a fault detection and diagnosis algorithm usually depends on the trade-off between robustness and sensitivity, so suitable metrics instead of only one should be used.

As lessons learned from this comparison, it can be stated:
1. Results getting from CWRU dataset always state very high scores.
2. New approaches should demonstrate their robustness to variations in operating data sets, fault size, training/test data sets etc.
3. Results should only be accepted as N-fold cross validated results to avoid effects by too precise tuning of algorithms.
4. Applicability to different benchmark data sets should be demonstrated to learn about the inter applicability problem of the individual approaches.

Table 1. Comparison of approaches on CWRU bearing dataset

Data selection				Feature extraction algorithms	Classifier	Results		Other Load tested	Fault size detection	Applied on other dataset	Reference
Load	Fault size	Tr/te ratio	N-fold Cross validation			Accuracy	Other results				
0	7	1:2	Y	DSLS-SVM	SVM	te:99.9	pr:99.96;re:99.95;F-s:99.9	--	--	Y	[10]
0	0,7,14,21	4:1	--	DBN+IWV	DBN+IWV	te:96.95	--	--	--	--	[23]
0	0,7,14,21	8:1	Y	LLRNN	softmax	te:96.2-99.5	--	--	--	Y	[40]
0	0,7,14,21,28	2:1	Y	EDAEs	softmax	te:97.18	pr:73.-100;re:67-100;F-s: 76.6-100	--	--	--	[34]
1	0,7,14,21	3:1	--	Semi-DBN	softmax	te:100	--	--	--	--	[24]
1	0,7,14,21	variant	Y	CNN	SVR	94.6-100	--	--	--	--	[30]
1	0,7,14,21	2:1	Y	EEMD/MPE+ SSDAE	softmax	99.6	--	--	--	Y	[38]
1	0,7,14,21,28	variant	Y	PCA	SVM-OAA	Mean:96.98	sp:99.2; re:100;ROC	--	--	--	[13]
2	21	variant	--	LCD/GDA	CRSVM	95-100	--	--	--	Y	[12]
3	7	9:1	Y	BPFG	SVM	99.05	--	--	--	--	[11]
3	0,7,14,21	10:19	--	CMFE	ESVM	100	--	--	--	--	[19]
0,1	0,7,14,21,28	1:1	--	DTCWPT	DBN model	te:98.75	--	Y	--	Y	[26]
1,2,3	0,7,14,21	variant	--	FFT+DACNN	softmax	mean:99.6	pr:90.81-100; re:79.88-100	Y	--	Y	[6]
0,1,2,3	0,7,14,21	1:1	Y	CWT/SVD	KMCSVM	above 95.6	--	Y	Y	--	[17]
0,1,2,3	0,7,14,21	1:1	--	HES	DBN	te:98--99.55	--	--	--	Y	[22]
0,1,2,3	7	1:3	--	WPT+DBN	softmax	te:99.58	--	--	--	Y	[25]
0,1,2,3	0,7,14,21	5:1	--	CNN	FC layer	mean: 99.79	--	--	--	Y	[27]

Data selection				Feature extraction algorithms	Classifier	results		Other load tested	Fault size detection	Applied on other dataset	Reference
Load	Fault size	Tr/te ratio	N-fold cross validation			Accuracy	Other results				
0,1,2,3	0,7,14,21	3:1	--	AWMSCNN	FC layer	97.97-99.98	--	Y	--	Y	[28]
0,1,2,3	0,7,14,21	4:1	--	FFT+IDSCNN	softmax	98.4	--	--	--	--	[29]
0,1,2,3	0,7,14,21	14:3	--	CNN	softmax	te: 99.41	--	--	--	Y	[31]
0,1,2,3	0,7,14,21	variant	--	SAE	softmax	mean:99.82	--	Y	--	--	[33]
0,1,2,3	0,7,14,21	1:9	Y	CLAE	softmax	te:99.73±0.15	--	--	--	--	[39]
0,1,2,3	0,7,14,21	132:5	Y	few-shot learning	FC layer	71.16-99.84	--	Y	--	--	[42]
0,1,2,3	7,14,21,28	2:3	Y	EEMD	ICDSVM	te:96.48-100	--	Y	Y	--	[9]
0,1,2,3	0,7,14,21,28	5:3	Y	WPT+Fisher's rankgin+KPCA	SVM with Gaussian	98.9-100	sp:98.5-100;re:98.6-100;PPV:98.5-100	--	--	--	[14]
0,1,2,3	0,7,14,21,28	1:1	--	BPSO-RFC	SVM	90.62-100	--	--	Y	--	[16]

Note: --: not mention; tr: training; te:test; sp: specificity; pr: precision; re:recall; F-s:F-score; PPV: positive prediction value; Y:yes; **EEMD:** ensemble empirical mode decomposition; **ICDSVM:** support vector machine optimized by inter-cluster distance; **DSLS-SVM:** deep stacking least square support vector machine; **GDA:** generalized discriminant analysis; **CRSVM:** chemical reaction support vector machine; **BPSO:** binary particle swarm optimization; **KMCSVM:** kernel matrix construction for support vector machine; **CMFE:** composite multiscale fuzzy entropy; **ESVM:** ensemble support vector machine; **DTCWPT:** dual-tree complex wavelet packet transform; **AWMSCNN:** adaptive weighted multiscale convolutional neural network; **IDSCNN:** deep convolutional neural networks and improved Dempster-Shafer; **SSDAE:** stacked sparse denoising auto-encoder; **DACNN:** domain adaptive convolutional neural network; **LCD:** local characteristic-scale decomposition; **DAE:** deep auto-encoder; **FFT:** fast Fourier transformation; **BPFG:** bandpass filter group; **OAA:** one against all; **WPT:** wavelet packet transform; **RFC:** regularized Fisher's criterion; **CWT:** continuous wavelet transform; **SVD:** singular value decomposition; **IWV:** improved weight voting; **HES:** Hilbert envelope spectrum; **FC layer:** fully connected layer; **SAE:** stacked auto-encoder; **SVR:** support vector regression; **CLAE:** class level auto-encoder; **EDAE:** ensemble deep auto-encoder; **KPCA:** kernel principal component analysis.

Regarding future research directions using CWRU bearing dataset, the following trends can be detected from the actual analysis:
1. Due to its excellent classification abilities, SVM and improved SVM still would be applied on CWRU dataset and other similar problems in practice in the next years.
2. More different structure of DL approaches can be expected.
3. Although TL approaches and few-shot learning are new now, new related developments can be expected in the near future.

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