ORIGINAL ARTICLE

Motor Fault Detection using Current and Sound: A Comparative Study

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Abstract: Early detection of motor faults can save the motor from subsequent deterioration into more severe conditions, and thus can save lot of maintenance costs. In this work, we have developed automatic motor fault detection system based on artificial neural-network (ANN) using two basic signals: current and sound. Motor condition is captured through current and sound signals which are then preprocessed, and a compressed feature vector is created in their frequency domain. Feature vectors from different motor conditions are used to train a neural network (NN). Once the training is done, the NN-system is ready to monitor motor health condition. Our experimental results show that our NN-based system can successfully detect different motor faults unto 99% accuracy. Both current and sound signals are thoroughly compared under different operating conditions of motors, where both single and three phase motors are considered. The hardware of the system comprised of low-cost CT (current transformer) and microphone that leads to a very cost effective solution. Detailed comparative results are presented that show the suitability of current, sound and their hybrid signal in different scenario. The robustness of the system is evaluated under different conditions such as environmental noise and system's parameters.

Keywords: Motor Faults, Fault Detection, Current & Sound Analysis, Neural Network

Introduction

Most of machinery used in the modern world operates by means of motors and rotary parts which can develop faults. It is of great value to a production company in the growing global market of today to be able to automatically detect or predict a failure in its machines. Now we can detect faults by many techniques that are reported in the literature [1-5]. The monitoring of the operative conditions of a rotary machine provides a great economic improvement by reducing the operational and maintenance costs, as well as improving the safety level [2-3]. Monitoring the motor condition is crucial to detect any fault in an early stage that can eliminate the hazards of severe motor faults. Faults have to be treated before totally damaging the machine and consequently it will reduce the maintenance cost and shutdown time. Thus, there is a growing need for a reliable, yet simple and low-cost technique to detect motor faults.

Faults in electrical motors occur in various ways such as electrical or mechanical. Mechanical imbalances and bearing faults account for a large majority of faults in a machine, especially for small-medium size machines. The common mechanical faults that occur in the motors are stator faults, rotor faults, bearing faults, eccentricity faults and mechanical looseness faults. These mechanical faults not only generate current and sound signature but also produce effects in the vibration and magnetic signals. According to [1] the major faults can be classified as: a) Stator inter turn fault, b) Rotor faults due to broken rotor bars, c) Static or dynamic air-gap irregularities, d) Bent shaft (dynamic eccentricity) and e) Bearing and gear box failures. Even though motor faults are internal, they could occur due to external effect like overheating caused by excessive dirt. Faults occurring in an induction motor produce one or more of the following symptoms: a)

Unbalanced air gap voltages, b) Increased torque pulsations, c) Decreased average torque, d) Increased losses and reduction in efficiency, e) Excessive heating, Leakage current in stator windings, and f) Change in rotor time constant. All the faults generate their own signature in different signal domains. Accordingly, we can use different types of sensors to sense the characteristic signals resulting from those faults. Various signal processing techniques are then applied on these signals to extract particular features which are sensitive to the presence of faults.

Faults diagnostic methods can also be classified based on major signal domains that can be summarized as follows: a) Motor-current signature analysis (MCSA); b) Acoustic noise measurements; c) Noise and vibration monitoring; d) Electromagnetic field monitoring, search coils, coils wound around motor shafts (axial flux-related detection). A number of techniques can be found in the literature for Motor current signature analysis (MCSA) [6-10], acoustic noise analysis [11-12], vibration analysis [12-15], electromagnetic field monitoring [16-17], infrared measurement, chemical analysis, temperature measurement [18], and partial discharge measurement [14].

Apparently, different types of faults produce their signatures in different signal domains that can be captured by domain-specific sensors. The captured signals can further be processed and some key-features can be extracted for detection of a specific fault. A suitable classifier such as neural network can use these key-features to classify a motor fault. In literature, a wide variety of fault-detection methods are reported. In [6], it was proposed to perform early fault diagnosis using high-resolution spectral analysis known as root-music algorithm of the stator current to detect bearing faults in electrical induction machine. The originality of their work relies on the use of high-resolution methods to detect modulations in the stator current. In [8-9] the fundamentals of motor current signature analysis (MCSA) are discussed for condition monitoring of an induction motor. In [9], the authors used fuzzy logic method and time-frequency domains called the smoothed pseudo winger-ville distribution (SPWVD) that was implied to analyze non-stationary signatures. In [10] fuzzy logic was applied to fault detection and diagnosis of induction motors where the motor condition is described using linguistic variables. They used Fuzzy subsets and the corresponding membership functions to describe stator current amplitudes, where a knowledge base, comprising rule and data bases, was built to support the fuzzy inference. In [19] the authors propose to perform early fault diagnosis using high-resolution spectral analysis of the stator current to detect bearing faults in electrical induction machine. From the literature it is apparent that current signal is most commonly used and it is the most reliable one.

In [12] bearing condition diagnosis is performed by using acoustic emission measurements. Acoustic emission depends on the vibration of machine. Above method investigates fault detection for rolling element bearings through acoustic signature analysis. In [11], an acoustic diagnostic technique was used for diagnosing electric machine insulation. By optimally launching an ultrasonic wave into a stator bar and using the conductor as a waveguide, it has been shown possible to interrogate the ground wall insulation and the critical interface region adjacent to the conductor. In [20] detection of induction motor operation condition by acoustic signal is presented which includes the four steps: transformation of the acoustic signal into a spectrum by fast Fourier transform, analysis the first band of the spectrum, establishing peak frequency-speed relation, and calculation of the unknown speed with Lagrange polynomial. In [21], gear fault diagnosis is presented using energy-based features of acoustic emission signals. The method can monitor and diagnose of machine conditions in spite of speed and load variations. The basic feature, termed here the energy index (EI), is a statistical measure of relative energy levels of segments of a time domain signal over a cycle. From the literature it is realized that the sound signal has a descent potential to solve fault detection problem. In addition it is a comparatively attractive solution because of its hardware simplicity and portability.

In [22] high order spectra of the radial machine vibration were used for fault diagnosis. In [12-13] detection of common motor bearing faults was performed using frequency-domain vibration signals and a neural network based approach. It presents an approach of using neural networks to detect common bearing defects from motor vibration data. The results show that neural networks can be an effective agent in the detection of various motor bearing faults through vibration signals. In [23] a DSP-based FFT-analyzer used for fault diagnosis of rotating machine based on vibration analysis. A DSP-based measurement system dedicated to the vibration analysis on rotating machines was designed and realized. In [24] introduces a new bearing fault detection and diagnosis scheme based on hidden markov modeling (HMM) of vibration signals. The technique allows for online detection of faults by monitoring the probabilities of the pre-trained HMM for the normal case. In [14] frequency spectrum of the bearing vibration signal is analyzed using a Fuzzy logic fault diagnosis methodology. The preliminary results show that fuzzy logic can be used for accurate bearing fault diagnosis if the input data is processed in an advantageous way.

In [25] the authors present the detection of voltage unbalance and rotor fault using an external stray flux sensor in a working three-phase induction machine. A simple external stray flux sensor was used for data processing at low-frequency resolution. In [26] the diagnosis of bar or ring rupture of a cage of asynchronous machine was presented. The authors used a modeling of the asynchronous machine by relating with the electromagnetic torque. The spectral analysis of the parameter leads to the diagnostic of a cage rupture by discriminating this fault from other faults, particularly mechanical ones. In [27] current signal frequency analysis was used for detection of air-gap eccentricity and bearing damage in induction motors. Magnetic flux density in the air-gap is calculated to get effect of faults on current signal. In [16] Electromagnetic flux monitoring was used for detecting faults in electrical machines. The electromagnetic flux measured in various locations of a 35-kW cage induction motor to provide useful information about faults was investigated.

In this work, we have developed a motor health monitoring system based on artificial neural network. We have used two important signals: current and sound to explore their capabilities in various conditions. At first, our system captures the signals, and a feature vector is created in frequency domain. Using the feature vector motor condition can be monitored through an artificial neural network. To do that the neural network need to be trained using feature vectors of know motor conditions. A detailed comparative result is presented which shows that both signals can deliver very high classification accuracy. In addition, we have presented comparative results under different motor conditions to explore the robustness of the system. These results show the effectiveness of the current, sound and their hybrid signals in various scenarios, and compare their relative strengths. At last, we have shown that the system is robust against different system's parameters. The proposed system is very attractive considering low cost setup, portability and accuracy. Our experimental results corroborate that we can achieve high classification accuracy as well as robustness by using hybrid signal which is not always possible from stand-alone current or sound signals. Rest of the paper is organized as follows: Section-2 describes different motor faults, signal collection, feature extraction and neural network classification. All the results and discussions are included in section 3 and conclusions are drawn in section 4.

Motor Faults & Their Detections

System overview

Motor fault detection deals with classification of signals captured through different sensors. In our experiments we have used current sensor (CT) and sound sensor (MIC) to monitor motor health condition. The overall system is illustrated Fig. 1. At first signals is captured through sensors, preprocessed, and feature vector is created. This feature vectors contains discriminative signatures of different motor health conditions. A neural network is trained using feature vectors from known motor conditions. After training is done, the system can classify any new data from different motor conditions.

Motor Conditions

A motor condition can be either healthy or faulty. Motor faults are divided into electrical and mechanical fault out of which mechanical faults are most common. Each fault type produces a unique signature in different signal domains such as current and sound that can be used for identification of faults. Short descriptions of common motor faults are:

- Mechanical imbalance: An unbalance effect occurs when the center of mass of motor does not coincide with the center of rotating. It can cause a high current flow together with different sound effect [2].
- Misalignment: Misalignment is a condition where the center lines of coupled shaft do not coincide.
- Mechanical looseness: Mechanical looseness usually involves mounts or bearing caps and almost always effect on current and sound signal.
- Bearing defects: Rolling elements bearings are the most common cause of machine failure. Motor performance is highly influenced by the bearings. Fault bearing can cause the system to function incorrectly and cause the vibration increase at some specific frequencies that result from bearing defects.
- Unbalanced Input voltage: This fault occurs when the line voltages of a three phase motor are not balanced.

Signal Collection

To detect the condition of a motor, both current and sound signals are collected. We have avoided direct measurement of the current using any current measuring instrument that can introduce unnecessary difficulty and cost. Instead, we have used a current transformer (CT) and we feed its output directly into the "Audio In" port of the computer. The software can then easily read the signals available at "Audio In". Most of the motor-faults induce some sort of variations or vibration in the rotating body, which creates an effect in the armature current through electro-magnetic coupling. Such variations in current signal contain the key information to discriminate different motor conditions. Thus, for our problem of fault detection we do not require exact value of the current. So a cheap CT is more practical as it provides us enough information such as variation of the current that reflects characteristics of any faulty condition. It should be noted that stator current is recorded only from one phase which appears to be effective in differentiating different fault conditions compared with currents from all three phases. On the other hand Sound signal is collected through a dynamic microphone which is an acoustic-to-electric transducer and its output is fed into the “Mic In” port of the computer. The software can easily access the signal available in the “Mic In” port.

Fig. 2 shows the CT and microphone used in this experiment. To collect a datum either from current or from sound, we record the signal for few second that comprised of 15000 samples. During the collection of data the speed of the motor was approximately maintained at 1400 rpm for both 3-Φ & 1-Φ motors.

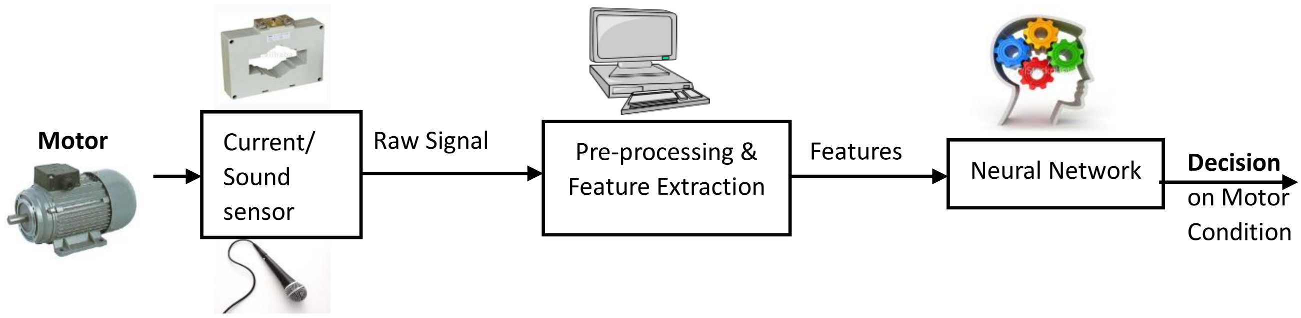

Figure 1. Typical motor current/sound fault recognition system structures.

Feature Extraction

Fig-3 describes the overall procedures of feature extraction. At first we collect input data where each datum consists of 1500 samples. We took the first feature $\bar{x}$ from time domain which is simple average of the samples. After down-sampling 5 times, the signal vector is reduced to 300 samples. To compute features in frequency domain Fast-Fourier Transform (FFT) is applied that gives us array of 300 complex vectors. We used only the absolute values of 300 complex vectors. After that only first half $f_x = [f_{x1}\, f_{x2} \ldots\ldots\ldots f_{x150}]$ of the array is kept, because absolute value of the FFT output is center-symmetric.

To form a reduced feature description, the vector is compressed into a new vector $C_x = [C_{x1} C_{x2} \ldots\ldots\ldots C_{x30}]$ such that $C_{x1} = f_1 + f_2 + \ldots\ldots + f_5$, $C_{x2} = f_{11} + f_{12} + \ldots\ldots + f_{15}$ and so on. Thus the vector C_x is formed which is then normalized as follows.

$$C_x^{'} = \left[\frac{CX_1}{\sum_{i=1}^{30} CX_i} \; \frac{CX_2}{\sum_{i=1}^{30} CX_i} \ldots\ldots \frac{CX_{30}}{\sum_{i=1}^{30} CX_i} \right]$$

Thus 30 frequency domain features are created. A total of 31 features are then used in our classification system.

$$T_f = [\bar{x} \;\; C_x^{'}]$$

Detection of Motor Fault by NN

After the feature extractions for all the data, features data are saved together with their class labels. The class labels are important information that needs to be supplied to the classifier during its learning process. For signal phase motor four different motor conditions are considered. Class labels are set to [1 0 0 0], [0 1 0 0], [0 0 1 0] and [0 0 0 1] for the healthy, fault1, fault2 and fault3 condition of the motor respectively. Similarly three conditions were considered for three phase motor, class labels were defined as [1 0 0], [0 1 0] and [0 0 1] for the healthy, fault1 and fault2 condition of the motor respectively.

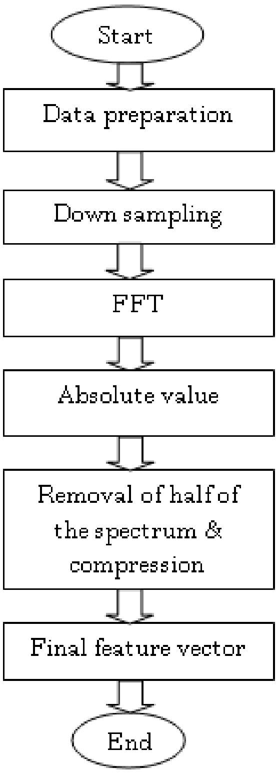

Figure 3. Flow chart for Feature extraction.

We have used neural network as a machine learning tool to learn different motor conditions from the data of current and sound. In a feed-forward neural network, information is passed from input layer to output layer between which one or more hidden layers exist. There are neurons in hidden and output layers. By passing through a neuron, a signal is transformed by an activation function. A signal from a neuron is passed to the neurons of next layer by multiplying some weight values. During the training, the weight vectors are refined in such a way that a desired output is generated indicating the class information of the input data.

In our neural network setup, we have used a 3-layer multi-layer perceptron (MLP) model as shown in Fig. 4. As the number of features is 31, the number of inputs for the network was set to 31. The number of neurons in the hidden-layer was set to 10. The number of output of the network was set to according to the number of class labels, which was '4' for single phase motor and '3' for 3-phase motor.

There are two steps for using neural network to detect motor fault: training and testing. The network is trained by using training data of different motor conditions. In this phase, the feature-vectors together with class labels are fed to the network through a number of iterations. Using optimizing algorithm, neural network update the network-weights by comparing its outputs and desired class-labels. After the learning is complete, the network is expected to deliver an output which is very close to the actual the label corresponding to a given input. During the testing phase, features of testing dataset are presented to the neural network. The outputs are then compared to the actual class information to find the accuracy of the trained neural network.

After successful completion of training and testing with good classification accuracy, neural network is ready to detect motor condition. The neural weight vectors from the training phase are saved for future classification of unseen data. To monitor the motor condition, sample signals are collected and features are extracted. The features are then fed to neural network input, and the decision for the new unseen data is then made from the output of neural network.

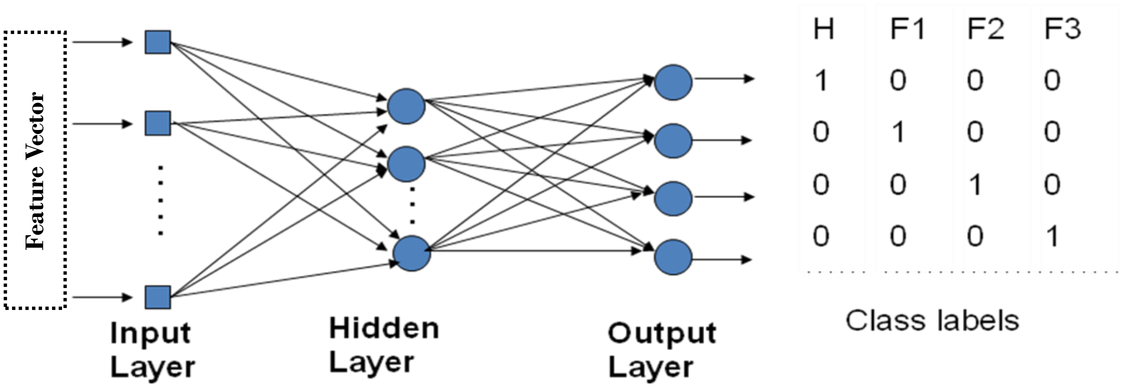

Figure 4. Block diagram describing NN classification

Experimental Results & Discussions

For performance evaluation of the proposed method, we have considered five motor conditions including healthy or normal condition. For each condition of motor 100 data were collected. The recorded data are divided into two categories: training set and testing set. The training dataset together with data class-labels was used in the training of the neural network. Then we have evaluated both the training set and the testing set to see if the neural network can properly classify the data. The testing dataset was not used in the neural network training so that we know how neural network can perform on the unseen data. All the classification results are averaged over several trials.

For all our experiments, we have used MATLAB in an Intel core-2 duo PC. As the numbers of features and hidden neurons were not very high, it required insignificant amount of memory and times to train and test data in neural network, which was few seconds for training and fraction of a second for testing each datum. To train the neural network, we have initialized the network weights with zero mean and unit variance isotropic Gaussian. There were different activation functions for the neurons in hidden and output layers which were 'tanh' and 'softmax' respectively. Unless specified 10 neurons were used in hidden layer. We have used Scaled Conjugate Gradient (SCG) algorithm to optimize the weights of neural network. By default, we have used 600 iterations during the training of network and a learning rate of 0.03 is used as the convergence-speed for learning the optimized network weights.

Signal Comparisons

Fig. 5 shows us time-domain current signals collected from different motor conditions. There are high similarity of signals among different motor conditions due to which it is not easy to discriminate them by observation with bare eye. However these discriminations become easier when we analyze the signals in frequency domain i.e., Fast Fourier Transform (FFT). Finally when we observe the signals in feature domain i.e., compressed representation of the FFT (Fig. 6), it is much easier to differentiate different motor conditions.

Similar observation is found for sound signal from four different motor conditions. Fig. 7 shows sound signals in time domain and Fig. 8 shows their features in frequency domain.

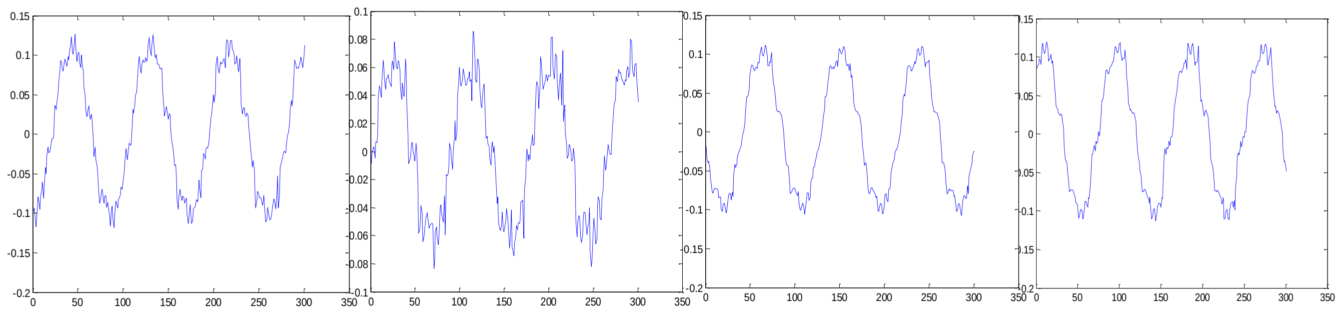

Figure 5. Current signals in time domain from 1-Φ motor for different conditions i) Healthy, ii) Bearing fault, iii) Mechanical imbalance, and iv) Mechanical looseness.

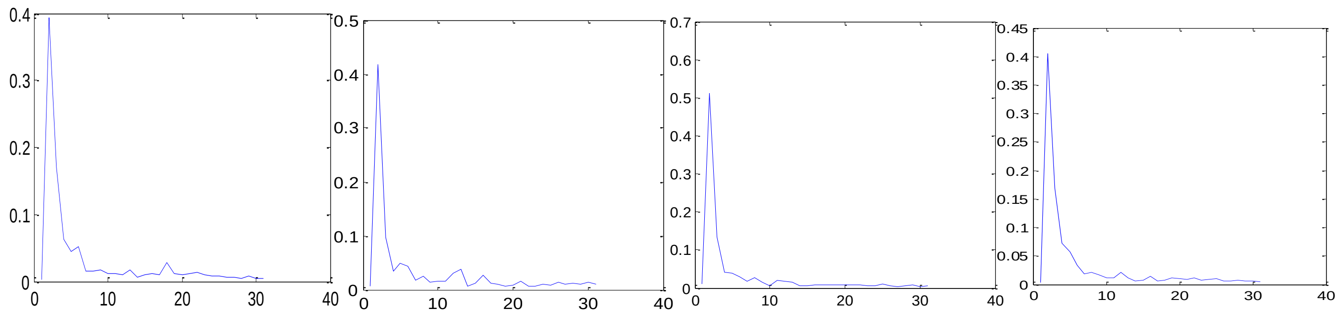

Figure 6. Compressed frequency spectrum of current signals from 1-Φ motor for four different conditions: i) Healthy, ii) Bearing fault, iii) Mechanical imbalance, and iv) Mechanical looseness.

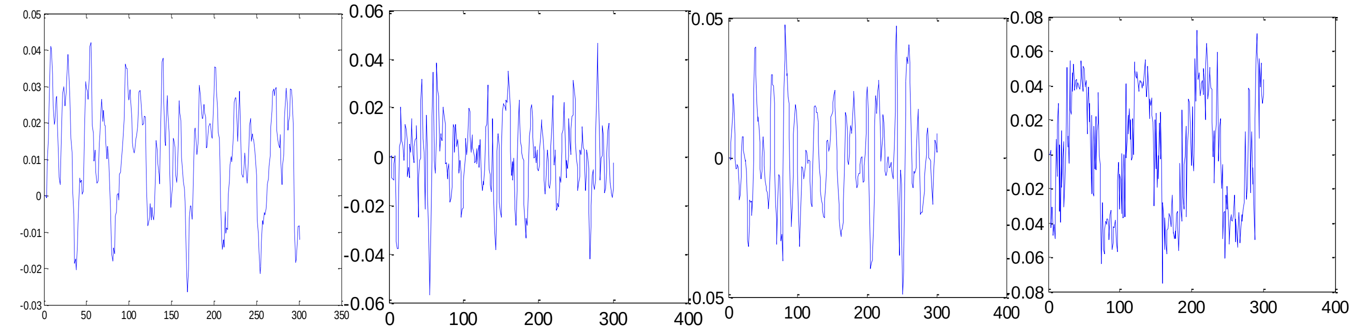

Figure 7. sound signals in time domain from 1-Φ motor for different conditions i) Healthy, ii) Bearing fault, iii) Mechanical imbalance, and iv) Mechanical looseness.

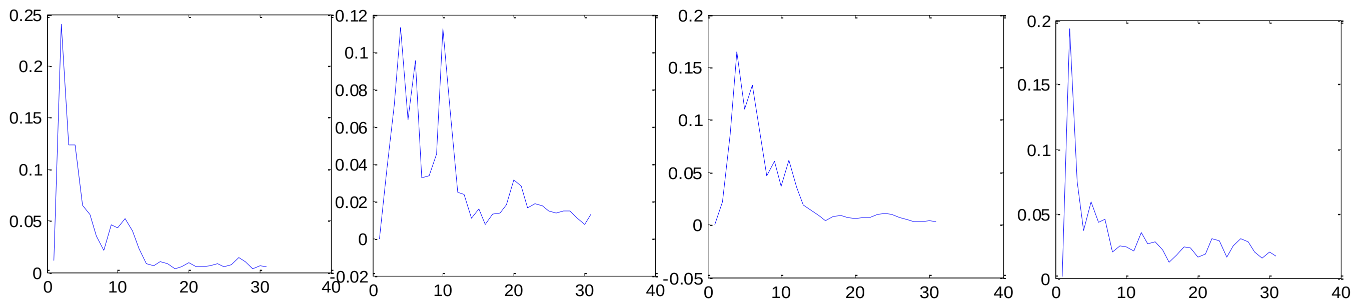

Figure 8. Compressed frequency spectrum of sound signals from 1-Φ motor for four different conditions: i) Healthy, ii) Bearing fault, iii) Mechanical imbalance, and iv) Mechanical looseness.

Comparing the signals in time domain it should be noted that sound signals are more discriminative for different motor faults compared to that of current signals. Similar properties are observed in frequency domain. This fact can be easily verified using classification results presented in the following section.

Following sections present comparative fault recognition results from current and sound signal. As the created faults are not identical for 1-Φ and 3-Φ motors, we will present them separately. The classification results using both training and testing sets are summarized. However, the results on testing set are of more importance and is considered as the basis of comparison, since the testing set are not used during training.

Comparative Results for 1-Φ Motors.

Table-1 shows the classification accuracy for 1-Φ motor conditions that compare two approaches using current and sound signals. We can see that the results on training sets are always better than that on testing sets. This is because of supervised learning of neural network where we have already provided class labels for the training data during the training phase. It is interesting to note that overall results from the sound signals are superior to that of current signals. This can be explained easily if we compare the FFT signals of current and sound for different motor conditions. By comparing Fig-6 and Fig-8, we can see that feature vectors of sound signal are comparatively better to discriminate different motor conditions. If we combine sound and current signal that constitute the hybrid signal, the classification result is better than current signal but similar to that of sound signal.

Table 1. Training and testing result in percentage

Current		Sound		Hybrid	
Train	Test	Train	Test	Train	Test
97%	**95%**	100%	**99%**	100%	**99%**

Confusion matrix is a powerful way to show the classification results in more details. It shows what percentage of data from each motor condition is classified accurately. It also shows how rest of the data is classified wrongly into other classes/motor conditions. Table -2 shows the confusion matrix for both current and sound signals. We can see that 96% and 98% of healthy data are classified correctly for using current and sound signals respectively. Only 4% and 2% of data are wrongly classified and got confused with Fault-2 and Fault-3 respectively. We can visualize some important conclusions from these matrixes. First, sound results are consistently better for different motor conditions. Second, current signal delivers inferior results for Fault-3, and some of the Fault-3 data are confused with Fault-2 data using current signal. This result can be explained by comparing visual similarity between Mechanical looseness is misclassified in Mechanical imbalance in Fig. (5-6).

Table 2. Confusion matrix from testing set

NN-input	**NN-Output**							
	Current				Sound			
	Healthy	Fault-1	Fault-2	Fault-3	Healthy	Fault-1	Fault-2	Fault-3
Healthy	96	0	4	0	98	0	0	2
Fault-1	0	98	0	2	0	100	0	0
Fault-2	2	0	96	2	0	0	100	0
Fault-3	0	0	10	90	0	0	0	100

Comparative results for 3-Φ motors.

Table-3 shows the classification accuracy for 3-Φ motor conditions that compare two approaches using current and sound signals. Motor conditions that are considered here are 'Healthy', 'Unbalance input voltage (fault-4)' and 'Mechanical lose (fault-3)'. Classification results from training set are again better than that of testing set, and the sound and hybrid signal provide better results.

Table 3: Training and testing result in percentage

Current		Sound		Hybrid	
Train	Test	Train	Test	Train	Test
100%	**98%**	100%	**100%**	100%	**100%**

Table 4 shows the confusion matrix of the classification results from testing set. We can see that the overall classification accuracy is better than that of 1-Φ motors even though faults are not identical. Also, using the current or hybrid signal, we can get 100% accurate accuracy. Whereas using current signal only a 2% of data are wrong classified and get confused between two classes: 'Healthy' and 'Fault-3'.

The overall results from single and three phase motors indicate that both current and sound signals are quite satisfactory considering an accuracy of 97-100%. However, classification accuracies are consistently higher (around 2%) for sound signal compared to current signal.

Table 4. Confusion matrix from testing set of 3-Φ motor

NN-input	NN-Output					
	Current			Sound		
	Healthy	Fault-4	Fault-3	Healthy	Fault-4	Fault-3
Healthy	98	0	2	100	0	0
Fault-4	0	100	0	0	100	0
Fault-3	2	0	98	0	0	100

Robustness of Fault Detection

Environmental Noise

In this section the robustness of the system is evaluated against environmental noise that can be critical issue for sound signal. We have recorded noisy sound from other motors, and add it to original recording of sound data. Fig. 9 shows that how the system accuracy using sound signal decreases when we gradually increase the amount of noise. When we add 5%, 10%, 15%, and 20% of noise, the classification results from the testing dataset become 100%, 97%, 85%, and 70% respectively. It is interesting to note that the training results are always 100%. This is because of the supervised nature of neural network training and the class labels are provided to the neural network during training process. For the cases of hybrid signal, the accuracies are 100%, 99%, 89% and 81% for adding 5%, 10%, 15%, and 20% of noise respectively. For both cases the results are satisfactory unto 10% of noise. Also, the result shows clear superiority of hybrid signal over standalone sound signal.

To look into details, the complete results for testing set using sound signal are shown in table 5. It is clear that the more noise we add, the more data from fault-1 and fault-2 got misclassified into healthy data. Unto 20% of noise we can get some satisfactory results after which results deteriorate significantly.

The details of the results from hybrid signal are summarized in table 6. The results show only fault-2 data are affected significantly if the noise level is 15% or more. The superiority of the hybrid signal can easily be linked to the fact that the hybrid signal contains the current signal which is unaffected by environmental noise. Thus, the hybrid signal can be considered a good alternative to stand-alone sound signal.

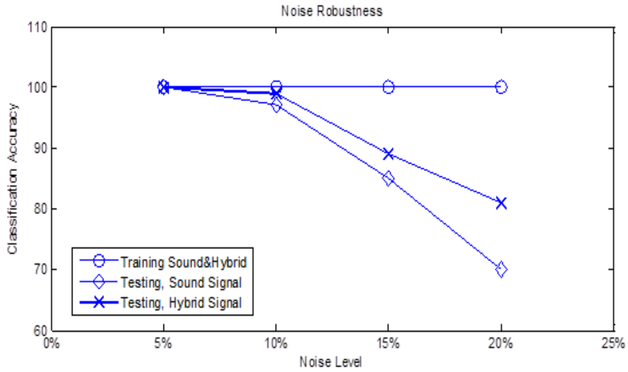

Figure 9. Robustness against environmental noise

Table 5. Confusion matrix using testing set of Sound signal for different levels of noise

	Noise level = 5%				**Noise level = 10%**			
	Healthy	Fault-1	Fault-2	Fault-3	Healthy	Fault-1	Fault-2	Fault-3
Healthy	100	0	0	0	100	0	0	0
Fault-1	0	100	0	0	1	99	0	0
Fault-2	0	0	100	0	11	0	89	0
Fault-3	0	0	0	100	0	0	0	100
	Noise level = 15%				**Noise level = 20%**			
	Healthy	Fault-1	Fault-2	Fault-3	Healthy	Fault-1	Fault-2	Fault-3
Healthy	100	0	0	0	100	0	0	0
Fault-1	15	85	0	0	65	26	0	9
Fault-2	45	0	55	0	45	0	55	0
Fault-3	0	0	0	100	1	0	0	99

Table 6. Confusion matrix using testing set of Hybrid signal for **different levels of noise.**

	Noise level = 5%				**Noise level = 10%**			
	Healthy	Fault-1	Fault-2	Fault-3	Healthy	Fault-1	Fault-2	Fault-3
Healthy	100	0	0	0	100	0	0	0
Fault-1	0	100	0	0	0	100	0	0
Fault-2	0	0	100	0	4	0	96	0
Fault-3	0	0	0	100	0	0	0	100
	Noise level = 15%				**Noise level = 20%**			
	Healthy	Fault-1	Fault-2	Fault-3	Healthy	Fault-1	Fault-2	Fault-3
Healthy	100	0	0	0	100	0	0	0
Fault-1	0	100	0	0	0	100	0	0
Fault-2	43	0	57	0	76	0	24	0
Fault-3	0	0	0	100	0	0	0	100

We could not evaluate noise effect on current data due to complexity of practical noise generation in current data, and it is hard to isolate them from noise free data. In fact the current data we collected might have some undesired harmonics (noise) coming from supply instead of generated locally in the machine. Thus, we could not verify the presence or absence of noise in the current data. For considering both sound noise and noise-free environment, hybrid signal is better choice in term of classification accuracy, but it requires more physical setup to collect the necessary signals.

Robustness over Motor Types, Ratings and Setup

We have finally considered some extreme cases where the training data and testing data are from completely different motors or their setups. At first, we considered the case where training data is collected from 1Φ motor to train a neural network, but then testing data collected from a 3Φ motor are presented to neural, and vice versa. The results using both current and sound signal are summarized in table 7.

We have also tested the case where training and testing data are from different motor ratings. The results are summarized in table 8 indicating a very poor performance. Finally we changed the motor setup where different grounds are changed. The results are shown in table 9 only for current data.

From the above results, the sound signal shows comparatively better results than the current signal. However, the results both signals are quite unsatisfactory. It clearly indicates a separate neural network need to be trained for each type of motors or setup to maintain classification accuracy above 95%. Once a neural network is trained, it cannot be used to monitor a different motor or setup.

Table 7. Robustness over motor types.

Trained by 1Φ, tested on 3 Φ		Trained by 3Φ, tested on 1Φ	
Current	Sound	Current	Sound
51	**50**	**46**	**61**

Table 8. Robustness over motor ratings.

Trained by 1Φ(1HP), tested on 1Φ(.75HP)		Trained by 1Φ(.75HP), tested on 1Φ(1HP)	
Current	Sound	Current	Sound
17	**55**	**32**	**63**

Table 9. Robustness over motor setup (current signal)

Trained and tested (ground: concrete floor)	Test (ground: table)	Test (ground: thick paper)
100%	45%	27.33%

Robustness over Training Parameters

In this section, the robustness of the method is tested against the changes in neural network parameters which are Number of Training cycle, Number of Hidden Neurons and Learning Rate. Thus, we can know how sensitive our method to different parameters and what are the optimum values to set for those parameters.

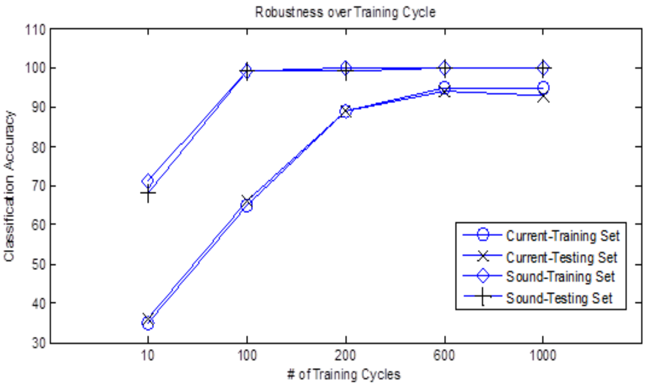

Figure 10. Robustness against the number of training cycles.

Fig-10 illustrates the robustness of the proposed method using both current and sound signal against the number of training cycles when the number of hidden neuron was 10 and learning rate was 0.3. For both signal types, around 600 training cycles are found to be adequate for proper learning of neural network. However, it is interesting to note that using sound signal require much less training cycles (near 100) to deliver satisfactory results. This result reconfirms the superiority of the sound signal, and we can again conclude that sound signal contains more discriminative characteristics compared with current signal.

Fig-11 shows the robustness of the system against the number of hidden neurons, while the number of training cycle was set at 600 and the learning rate was set at 0.3. The results corroborate that the neural network does not need much hidden neurons to get satisfactory results. Increasing the number of hidden neurons beyond 10 is unnecessary and it may decrease the performance as seen for the case of current signal. Less demand of hidden neurons indicate less complexity in the information encoded in the signal.

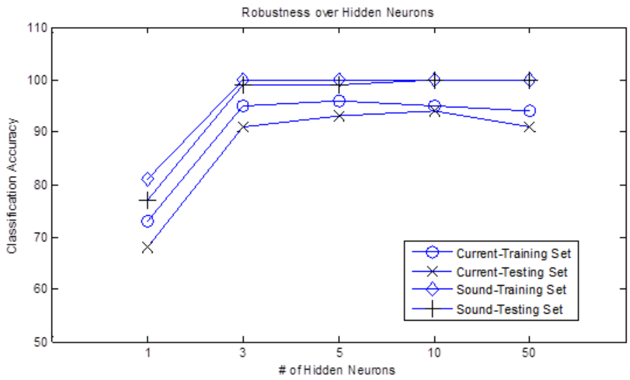

Figure 11. Robustness against the number of hidden neurons.

Finally, we have evaluated system's performances for different learning rates, while setting the number of training cycle at 600 and the number of hidden neuron at 10. Fig. 12 summarizes these results. There was no noticeable performance drop when the learning rate was set too low. We have found no significant performance variation when learning rate is set at 0.3 or above that indicates system's robustness against this parameter.

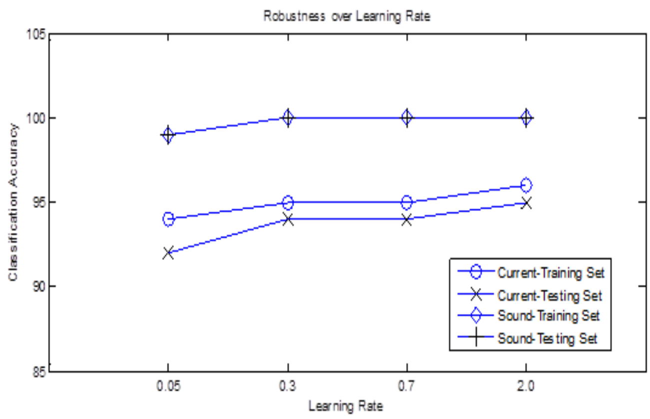

Figure 12. Robustness against the learning rate.

Conclusion

In this work, an artificial neural network based system is developed to monitor motor health condition. Both single and three phase motors are investigated in five different motor conditions. Our system shows promising performance unto 99% of classification accuracy. We have extensively compared two basic signals: current and sound, which contain valuable information regarding motor health. Detailed experimental results indicate that both sound and current signal can deliver satisfactory results with classification accuracy from 97% to 100%. However, the sound signal consistently performs 2% better than the current signal that confirms that the sound signal contains richer information compared with the current signal. We have also included the results from hybrid signal that contains both current and sound signals. The hybrid signal can deliver results similar to that of sound signal.

Experimental results are also included to show the noise robustness of the system. Sound based method can deliver satisfactory results unto 10% of environmental noise. On the other hand, current based method is totally unaffected by noise, can deliver better results in the case of more noise. Considering both noise-free and noisy conditions, hybrid signal is better choice in terms of classification accuracy. This is because the hybrid signal can retain good accuracy by using richer information in sound signal for noise-free environment, while in noisy environment it performs decently using current signal. However, the hybrid signal requires more physical setup to collect both current and sound signals.

In real world, the current/sound signals vary depending on motor types, rating, physical setup etc. In order to realize how the proposed system will perform on deviating condition (different motor setup from that of training), we have included some interesting cases where training data are collected from one motor setup/type and testing is conducted on different ones. The results indicate that for an optimum performance, the neural network must be trained separately for each combination of motor type (single/three phase), rating (motor power) and setup (base where motor is physically connected). Finally we have shown the robustness of the system against parameters of neural network. These results indicate that our system performs decently well when the parameters are changed moderately.

The hardware required for the proposed method consists of low cost transducer such as CT and microphone which makes it very attractive solution for real world application of motor health monitoring. The overall classification performance based on acoustic method is superior. In addition acoustic method requires only a microphone which is simpler and more portable compared with the current method that requires a CT circuit to establish. Thus acoustic method is more attractive because of its simplicity and portability. However, we have discovered that hybrid signal is more robust to environmental noise at expense of more physical setup.

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