ENGI 9330 – Abnormal Situation Management & Fault Detection

Spring 2019

Project Report on

Support vector machines & discrete wavelet transform based fault detection of induction motor

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Due: 08th August 2019

Abstract

This term project involved in fault detection of induction motor. Two types of the fault have been detected, namely, bearing fault and one broken rotor bar fault. Experimental process data have been used in the present study. Discrete Wavelet Transform (DWT) has been used first to convert data into the frequency domain and extract data features. Data Matrix has been developed for both healthy and faulty process data. Further, faulty data then used to train the classifier by using SVM model.

Acknowledgement

We would like to show our sincere gratitude to Dr. Syed Imtiaz for his guidance and valuable feedback, which helps to improve the overall quality of the project. Last but not the least Kawsar Zaman Shafi, Graduate Research Assistant, Memorial University, for his insights on these data as he collected the data.

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Chapter 1 Introduction

1. Rational of the topic

Automated process systems have become large and complicated. A process upset or any abnormality may cause high economic losses, environmental damage and human loss. Therefore, it is essential to timely and precisely detects any process variation, which might result in abnormality. The main objective of fault diagnosis is fault detection, isolation, identification, and bringing back the process to its original operating conditions by taken appropriate measures.

It is vital to maintain continuous operation of induction motor in industrial processes. To extract data features and to convert the data into the frequency domain, DWT is applied in the present study. These unknown features might include faults and process abnormalities. Researchers are developing many new methods of fault detection, among which Support Vectors Mach is widely appreciated. The SVM algorithm can be trained using known faulty features from process data. This trained algorithm can then be used with new data to identify faults in the system [1], [2].

Early fault detection of a plant's induction motor is vital to keep the work of any plant steady and prevent downtime. There are many sorts of faults which can occur in an induction motor. The bearing fault is the most common among them. Among all the common faults of induction motor, about 40% of the faults are bearing failures [3]. One broken rotor fault has also been considered. Generally, these faults are detected and diagnosed using advanced signal processing methods such as Hilbert Transform and Wavelet transform. Fault detection using process data falls under the knowledge-based approach, and hence, hybrid machine learning such as DWT combined with SVM analysis is attractive and promising for use in the industry [2].

2. Problem Identification

Detecting bearing and broken rotor faults of an induction motor is a challenging task. The present study explores a hybrid formalism to detect faults, consists of DWT and SVM. DWT is used to reduce the features of the data and SVM is used to train the model, which subsequently detect the fault in the system.

3. Objectives

The goal of this project is to detect a fault in an induction motor. This work focuses on combining DWT and SVM to detect two different faults in the induction motor.

- Review and application of fault detection techniques into a real-life problem.
- Application of DWT to reduce features in induction motor data
- Application of SVM to train the model using faulty experimental data
- Application of hybrid formalism (DWT & SVM) to detect a faulty condition in induction motor

4. Scope

The project solely involves in the fault detection of induction motor. It also helps to understand the suitable method to identify the faults. Two sets of data are collected, one from a healthy motor and the other from a motor with fault. Current and vibration from the motors are recorded. These data of the induction motors are used to train the model, which helps to detect the faulty conditions.

Chapter 2 Literature review

The project focuses on fault classification and identification. Therefore, the present chapter illustrates detailed review about DWT and the machine learning classification technique, i.e. SVM.

Machine learning classification methods commonly a supervised learning technique and used to classify the raw data, therefore these methods mostly involved in machine learning, data-driven models. There are several algorithms used to classify the data such as support vector machine (SVM), principal component analysis (PCA), KNN and Tree. However, in the present study, SVM has been exploited.

2.1 Introduction of Discrete Wavelet Transform

Wavelet transform is not only limited to single function in all frequency components. It can decompose a signal into wavelet which will be in time-frequency analysis [4], [5]. Using the wavelet expansion theory, any function can be expressed as a sum of basis elements as shown in equation (1) [5].

$$f(t) = \sum_{k=-\infty}^{\infty} c_k \varphi(t-k) + \sum_{k=-\infty}^{\infty} \sum_{j=0}^{\infty} d_{j,k} 2^{\frac{j}{2}} \varphi\left(2^j t - k\right) \quad (1)$$

In the above equation c_k refers to approximation coefficient, j is the scale parameter or frequency range and $d_{j,k}$ illustrates detail coefficient. Parameter k shows the time translations of wavelet basis function φ and it can be defined as shown in equation (2)

$$\varphi(t) = \sum_{k=-\infty}^{\infty} h[k] \sqrt{2\varphi(2t-k)} \quad (2)$$

In the above equation, $h[k]$ is a finite sequence. Using above equation each coefficient of can be estimated as the inner product of function and basis element. Equation (1) coefficients can be estimated as shown below.

$$c[k] \equiv c_k = \int_{-\infty}^{\infty} f(t)\varphi(t-k)dt \quad (3)$$

$$d_j[k] \equiv d_{j,k} = \int_{-\infty}^{\infty} f(t) 2^{\frac{j}{2}} \varphi\left(2^j t - k\right) dt \quad (4)$$

The signal decomposition using DWT into sets of wavelets takes place. Each wavelet contains original signal at particular frequency band and wavelet signal reflects the time evolution of the frequency components of the original signal [5]. Due to decomposition two coefficient, namely, approximation coefficient $c[k]$ and detail coefficient $d_j[k]$ can be determined.

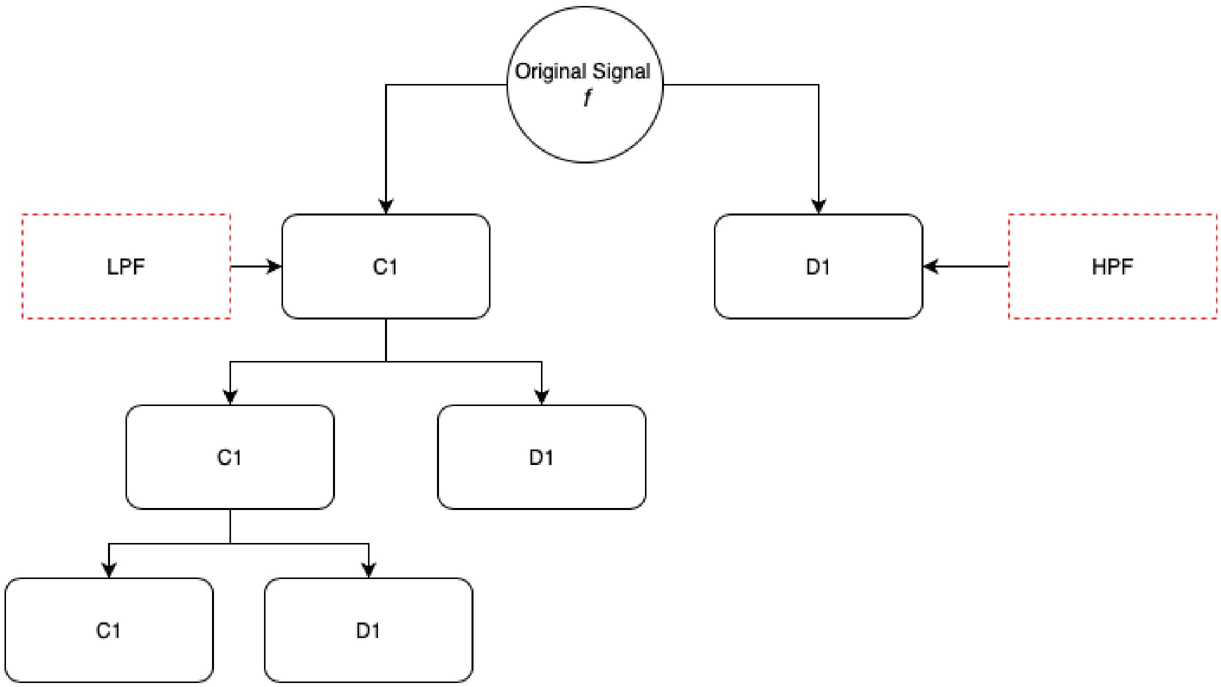

Figure 1: *Decomposition of original signal into set of wavelets*

Each decomposition sequence stage has two filters i.e. low-pass filter (LPF) and high pass filter (HPF). The prior filter (scaling function) provides low frequency signal and the latter (mother wavelet) provides high frequency signal as illustrated in figure 1. Each successive decomposition step corresponds to certain resolution. This process might be iterative with successive approximations being decomposed, known as wavelet decomposition tree [6]. As illustrated in figure 1, DWT carries out the filtering process, which provides flexibility for the simultaneous analysis of transient evolution. In contrast with other techniques, the DWT computation is low, and it is available in commercial packages which do not require any sophisticated algorithm for its application [5].

2.2 Supervised classification and machine learning algorithm

Process data helps to train the monitoring scheme, known as process history-based methods [7]. A large percentage of historical data is used to construct the monitoring scheme for fault detection and diagnosis, known as feature extraction. According to Venkatasubramanuan [7], data-based methods mainly divided into two categories, namely, qualitative and quantitative methods. The prior method includes techniques such as What if analysis, HaZop analysis, etc., while the latter includes statistical methods such as PCA, SVM etc.

The MATLAB Classification Learner application trains models to classify data. This application can explore supervised machine learning using various classifiers such as exploring data, selecting its features, specify validation schemes, train models, and assess results. It can also help to do automated training to search for the best classification model type, including decision trees, discriminant analysis, support vector machines, logistic regression, nearest neighbours, naive Bayes, and ensemble classification. It helps to select the best suitable model for the data by performing model assessment and model comparisons using ROC curves and confusion matrices [8].

Support Vector Machines (SVM) are classification and regression tool which have been derived from statistical learning theory. It is based on optimal linear separating hyperplane that is fitted to the training patterns of two classes within a multi-dimensional feature space. The optimization problem must rely on structural risk minimization. It aims to maximize the margins between the hyperplane and closest training samples. Suppose, if two classes are non-separable, SVMs employ the kernel trick where a positive definite kernel function is used to map the input data into a high dimensional transformed feature space. SVM based classification process tutorial can be found in [9]. The success of SVMs starts when they do not require an estimation of statistical distributions of classes to carry out the classification task, but they define the classification model by exploiting the concept of margin maximization [10]. Compared to other approaches such as Artificial Neuron Network, SVMs exhibit higher generalization capability, robustness to Hughes phenomenon, the lower effort required for model selection in the learning phase and optimality of solution obtained by the learning algorithm. The statistical methods can be used to drive the data-based model. It has both univariate and multivariate techniques [11]. The former includes the Shewhart control chart, exponentially weighted moving average (EWMA) control chart and cumulative sum (CUSUM) control chart. The Shewhart chart is the most widely used univariate control chart and also known as the mean chart. The upper control limit (UCL) and lower control limit (LCL) of the Shewhart control chart are calculated from the features of the data such as mean and standard deviation. The advantage of univariate monitoring techniques is the ease of use [12]. However, if we see the disadvantages, one of them is that it does not consider the change in operating condition while taking a decision which can result in false alarms. Another disadvantage is needing an individual chart to monitor a variable which adds more complexity. Hence, only a few quality variables are possible to monitor using univariate techniques.

In literature, authors proposed various SVM methods, a method describe in [13] which uses a conjugate gradient algorithm to solve SVM-QP problem. Another method proposed in [14] which shows minimal sequential optimization to solve SVM-QP problem. However, in the current study [9] suggested method has been used. In this method kernel function of SVMs used. It is associated with two parameters associated with kernels: D and γ. There is one more parameter C, which is related to the degree of the polynomial. These parameters play an important role in SVM performance. Therefore, the selection of each of the parameter is important and improper selection may cause underfitting or overfitting issue [2]. Nonetheless, there is a guideline available to choose the parameters using cross-validation [9].

Chapter 3 Methodology

This project is based on a data-driven model using DWT and SVM. As illustrated in figure 2, the flow chart depicts all the steps which have been taken to train the offline model, which can able to detect online data faults. As illustrated in figure 2, Step 1 shows the collection of data, which is the experimental data obtained from [15]. Once the data is collected, it has been divided into different sets. In each set DWT is applied to convert it into the frequency domain and extract the features of it. Once the features have been obtained, we train the data-driven model using different sets of data, sets consist of healthy, broken rotor fault and bearing fault. The model can detect offline data faults in a system.

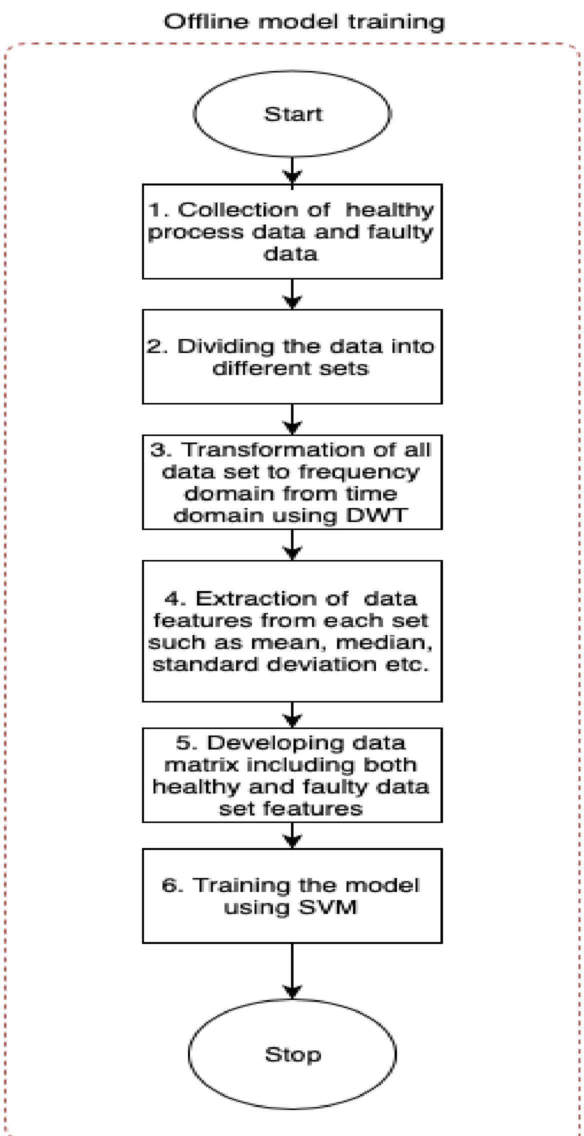

Figure 2: Offline model training

Chapter 4 Data driven model

Wavelet Analyzer application in MATLAB is used to perform DWT on the experimental data obtained from [15]. The following steps has been taken to pre-process the data.

Figure 3: Steps performed in wavelet analyzer application

DWT decomposition for one set of healthy data of current and vibration are shown in figure 4 and 5 respectively. As depicted, the original signal has been passed through HPF and LPF and gets broken into wavelets.

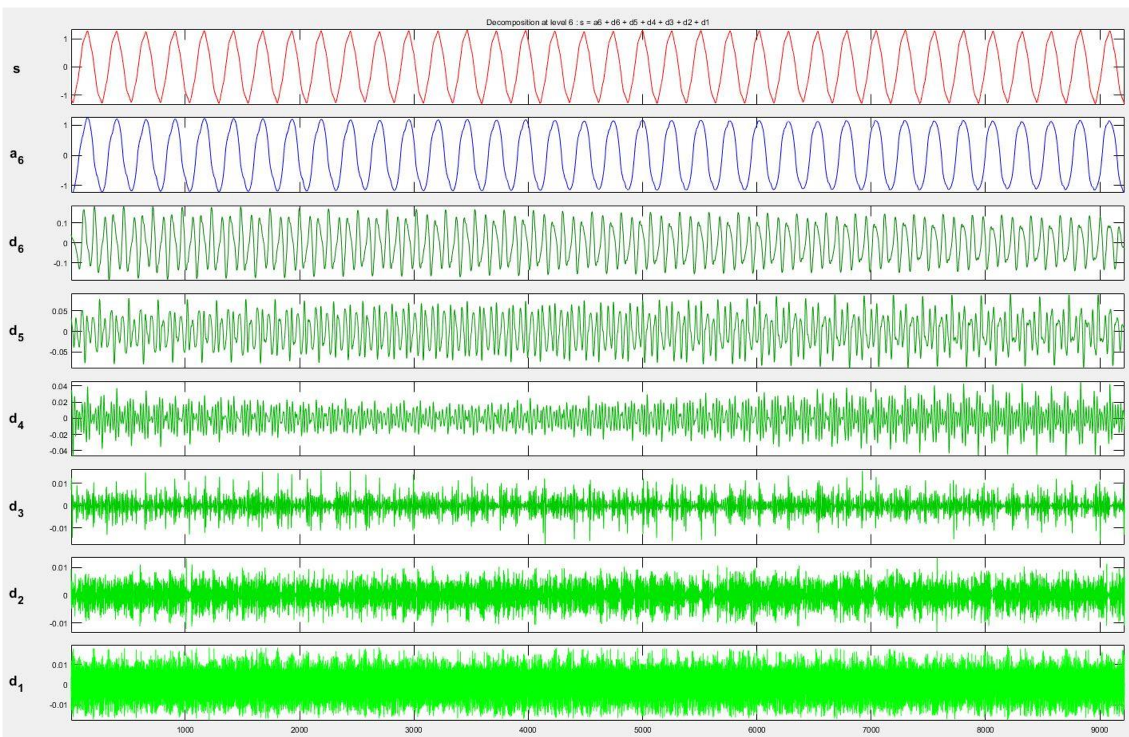

Figure 4:DWT transformation of set one of healthy current data

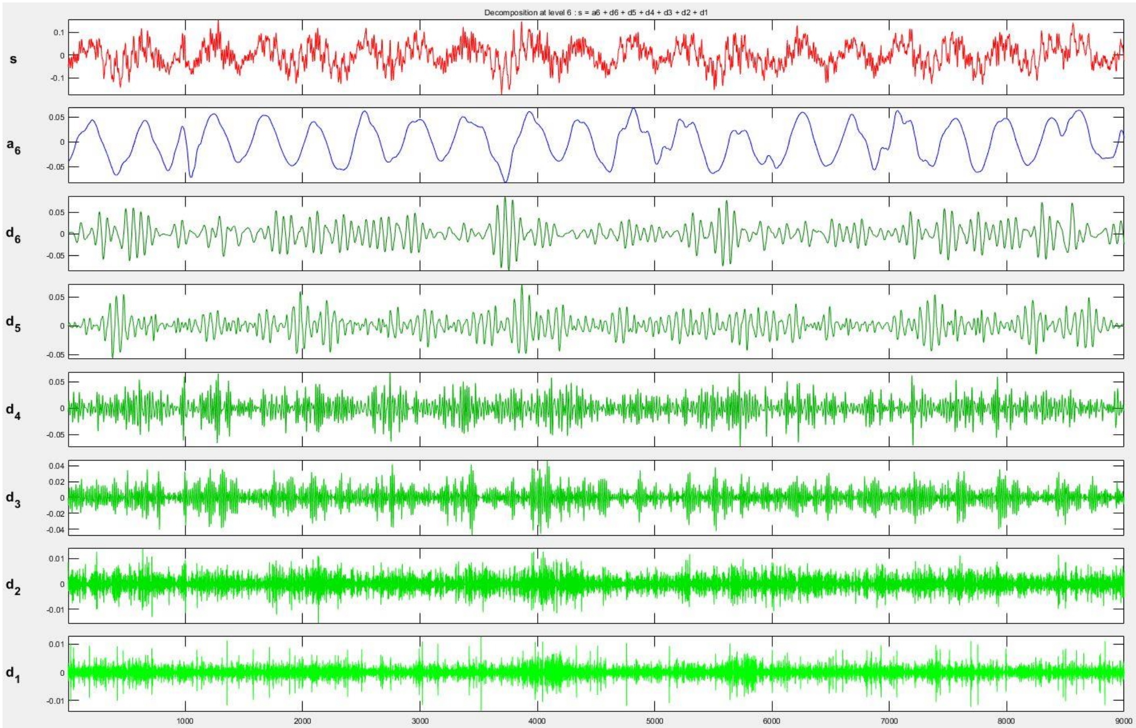

Figure 5: DWT transformation of set one of healthy vibration data

As shown in Table 1, each set of data of phase 2 current is analyzed with the application as mentioned earlier, and statistical features are consisting of healthy data, bearing fault and broken rotor fault. Similarly, for vibration data, the same procedure has been applied, which is shown in Table 2.

Table 1:Features extracted from data sets of phase-2 current data

Current Data											
		Extracted Features									
Set Number	Type of data	Mean	Median	Maximum	Minimum	Standard Deviation	Median Absolute Deviation	Mean Absolute Deviation	L1 Norm	L2 Norm	Maximum Norm
1	Healthy	-0.00051	0.001079	1.324	-1.325	0.8598	0.8559	0.7755	7147	82.53	1.325
2	Healthy	-1.8E-05	0.002158	1.329	-1.323	0.8611	0.8567	0.7766	7157	82.66	1.329
3	Healthy	0.002305	0.005665	1.321	-1.331	0.8589	0.8548	0.7747	7140	82.45	1.331
4	Healthy	0.001149	0.002428	1.36	-1.318	0.8598	0.8554	0.7754	7146	82.53	1.318
5	Healthy	0.002051	0.005395	1.314	-1.319	0.858	0.8535	0.7739	7132	82.37	1.319
6	Healthy	0.001848	0.003237	1.317	-1.315	0.8568	0.8527	0.7729	7123	82.25	1.317
7	Healthy	0.001271	0.002158	1.317	-1.321	0.8561	0.8529	0.7722	7117	82.18	1.321
8	Healthy	0.002387	0.002428	1.313	-1.316	0.8557	0.8513	0.7718	7113	82.14	1.316
9	Healthy	0.00162	0.002697	1.309	-1.316	0.8549	0.8497	0.7711	7106	82.07	1.316
10	Healthy	0.001586	0.003507	1.316	-1.315	0.8542	0.8513	0.7705	7101	82	1.316
1	Bearing Fault	0.001072	0.004316	1.509	-1.499	0.9629	0.9468	0.868	7999	92.44	1.509
2	Bearing Fault	0.001515	0.002697	1.521	-1.531	0.9761	0.9614	0.8795	8106	93.7	1.531
3	Bearing Fault	0.000419	0.001079	1.484	-1.495	0.9572	0.9409	0.8629	7952	91.89	1.495

4	Bearing Fault	0.001221	0.005395	1.516	-1.514	0.9714	0.9565	0.8754	8068	93.25	1.516
5	Bearing Fault	0.001059	0.004316	1.483	-1.49	0.9562	0.9398	0.862	7945	91.79	1.49
6	Bearing Fault	0.001063	0.003776	1.499	-1.507	0.9704	0.9549	0.8745	8060	93.15	1.507
7	Bearing Fault	0.001239	0.001618	1.485	-1.484	0.9555	0.9392	0.8614	7939	91.73	1.485
8	Bearing Fault	0.000493	0.003507	1.497	-1.501	0.9659	0.9508	0.8706	8024	92.72	1.501
9	Bearing Fault	0.001269	0.004586	1.469	-1.476	0.9544	0.9379	0.8603	7929	91.61	1.476
10	Bearing Fault	0.000879	0.004046	1.488	-1.504	0.9643	0.9492	0.869	8009	92.56	1.504
1	Broken Rotor Bar Fault	0.001503	0.004316	1.3	-1.303	0.8473	0.8448	0.7633	7035	81.34	1.303
2	Broken Rotor Bar Fault	0.000256	0.002158	1.302	-1.3	0.8472	0.8438	0.7634	7036	81.33	1.302
3	Broken Rotor Bar Fault	0.00168	0.004046	1.303	-1.3	0.8461	0.8435	0.7623	7026	81.22	1.303
4	Broken Rotor Bar Fault	0.001067	0.003507	1.299	-1.303	0.8469	0.844	0.7631	7032	81.3	1.303

5	Broken Rotor Bar Fault	0.001054	0.004855	1.299	-1.302	0.8466	0.8438	0.7627	7029	81.27	1.302
6	Broken Rotor Bar Fault	0.000888	0.003237	1.302	-1.303	0.8461	0.8429	0.7622	7025	81.22	1.303
7	Broken Rotor Bar Fault	0.001068	0.002428	1.3	-1.297	0.8464	0.8419	0.7625	7028	81.25	1.3
8	Broken Rotor Bar Fault	0.001182	0.005665	1.302	-1.306	0.8463	0.844	0.7626	7028	81.24	1.306
9	Broken Rotor Bar Fault	0.001147	0.005125	1.309	-1.319	0.8466	0.8435	0.7628	7030	81.27	1.319
10	Broken Rotor Bar Fault	0.000941	0.004046	1.296	-1.299	0.845	0.9394	0.7613	7016	81.12	1.299

Table 2:Features extracted from data sets of z-axis vibration data

Vibration Data											
		Extracted Features									
Set Number	Type of data	Mean	Median	Maximum	Minimum	Standard Deviation	Median Absolute Deviation	Mean Absolute Deviation	L1 Norm	L2 Norm	Maximum Norm
1	Healthy	-4.1E-05	-0.002	0.154	-0.172	0.04956	0.034	0.04008	360.7	4.702	0.172
2	Healthy	0.001614	0.002	0.15	-0.15	0.04429	0.03	0.03551	319.7	4.205	0.15
3	Healthy	-0.00029	0	0.142	-0.172	0.04852	0.034	0.03961	356.4	4.603	0.172
4	Healthy	0.001062	0.002	0.136	-0.176	0.04623	0.032	0.03673	330.7	4.387	0.176
5	Healthy	-0.00121	0	0.132	-0.168	0.04563	0.032	0.03679	330.9	4.33	0.168
6	Healthy	0.001165	0	0.136	-0.152	0.04502	0.03	0.03618	325.5	4.272	0.152
7	Healthy	0.000572	0	0.116	-0.15	0.04172	0.03	0.03391	305.2	3.958	0.15
8	Healthy	-0.00047	0	0.134	-0.144	0.04444	0.03	0.03562	320.6	4.216	0.144
9	Healthy	0.000428	0	0.138	-0.14	0.04324	0.03	0.03506	315.5	4.102	0.14
10	Healthy	0.00099	0.002	0.152	-0.162	0.04383	0.03	0.03488	314	4.159	0.162
1	Bearing Fault	0.02147	0	9.6	-10	1.128	0.4	0.7228	6485	107	10
2	Bearing Fault	0.02231	0	7.6	-7.8	1.084	0.4	0.7104	6372	102.8	7.8
3	Bearing Fault	0.02293	0	9	-6.6	1.05	0.4	0.6849	6144	99.67	9

4	Bearing Fault	0.02044	0	6.8	-6	0.983	0.4	0.6179	5539	93.27	6.8
5	Bearing Fault	0.01976	0	8.2	-8.4	1.064	0.4	0.6611	5929	100.9	8.4
6	Bearing Fault	0.01849	0	7.2	-7.4	0.9665	0.4	0.5891	5279	91.71	7.4
7	Bearing Fault	0.02227	0	12.2	-10.6	1.339	0.4	0.8295	7447	127.1	12.2
8	Bearing Fault	0.02264	0	11	-9.4	1.329	0.4	0.8234	7391	126.1	11
9	Bearing Fault	0.01702	0	8.2	-7.6	1.149	0.4	0.7154	6422	109	8.2
10	Bearing Fault	0.02102	0	10	-10.4	1.175	0.4	0.7147	6411	111.5	10.4
1	Broken Rotor Bar Fault	5.96E-05	-0.002	0.134	-0.138	0.04089	0.028	0.03295	296.5	3.879	0.138
2	Broken Rotor Bar Fault	0.001283	0	0.158	-0.128	0.04446	0.03	0.03606	324.4	4.219	0.158
3	Broken Rotor Bar Fault	0.001544	0.002	0.158	-0.15	0.05	0.036	0.04063	365.7	4.746	0.158
4	Broken Rotor Bar Fault	-2.7E-05	-0.002	0.18	-0.138	0.04836	0.034	0.03899	351	4.587	0.18

5	Broken Rotor Bar Fault	0.000532	0	0.132	-0.15	0.03936	0.026	0.03132	281.8	3.734	0.15
6	Broken Rotor Bar Fault	0.001224	0	0.168	-0.15	0.04641	0.032	0.0375	337.4	4.404	0.168
7	Broken Rotor Bar Fault	0.00081	0	0.13	-0.132	0.03979	0.028	0.03221	289.8	3.776	0.132
8	Broken Rotor Bar Fault	0.000614	0.002	0.152	-0.13	0.04444	0.03	0.03567	321	4.216	0.152
9	Broken Rotor Bar Fault	0.000761	0	0.182	-0.146	0.04456	0.03	0.0361	324.8	4.228	0.182
10	Broken Rotor Bar Fault	-0.00098	0	0.136	-0.17	0.04579	0.032	0.0372	334.7	4.344	0.17

Chapter 5 Results and discussion

The experiment study conducted by [1] has two different motors for the tests. Firstly, for healthy data collection and another for faulty conditions. Total data points for each case are 90,000 which is divided into 10 set sets. DWT has been chosen to apply to the data taken from the published work to extract the features. The advantage of DWT is it uses a variable sized regions windowing technique as compare to fixed-time window technique such as Fourier transform. Therefore, a signal can be approximated with different scales rather than using a fixed windowing technique [4].

Later, these features are used to train and test the model using SVM. The first motor has mechanical faults, and another has electrical faults. Db4 wavelet is considered for 6^{th} level decomposition, and it is from the Daubechies family with four vanishing moment. In real life application, it is easy to monitor current as compared to vibration data. The current data can be measured at the terminal of the motor, whereas vibration signals require a vibration sensor to capture the data. It is also costly and complicated to gather vibration data, especially in a harsh environment [1].

In the current study we have used 10 statistical features: mean, maximum value, minimum value, median, standard deviation, median absolute deviation, mean absolute deviation, L1 norm, L2 norm and maximum norm. The proposed features are shown in table 1 and 2. These features are used to train and test the model using SVM

Features from the data sets are used to train the SVM classifier with 5-fold cross-validation. Training accuracy at different kernel functions is listed in table 3 and 4. It is found that the accuracy level is low in fine Gaussian SVM as compared to others in current data sets. However, if we look on vibration signal data cubic SVM has the highest accuracy.

Table 3:Trained accuracy level of current data SVM model at different kernel function

SVM Kernel Function	Accuracy level
Linear SVM	96.7 %
Quadratic SVM	96.7 %
Cubic SVM	96.7 %
Fine Gaussian SVM	83.3%
Medium Gaussian SVM	96.7 %
Coarse Gaussian SVM	96.7 %

Table 4:Trained accuracy level of vibration data SVM model at different kernel function

SVM Kernel Function	Accuracy level
Linear SVM	66.7 %
Quadratic SVM	86.7 %
Cubic SVM	86.7 %
Fine Gaussian SVM	70 %
Medium Gaussian SVM	80 %
Coarse Gaussian SVM	70 %

The confidence matrix of all the kernel functions of current data are shown in figure 6 and 7 whereas figure 8-11 shows the confidence matrix obtained for all the kernel functions of vibration signals.

Model accuracy is illustrated in the confidence matrix. Figure 6 shows that bearing fault has been successfully identified in all cases, however, the trained model faced difficulty isolating healthy data from data with broken rotor bar fault 9% of the cases. This results in the overall average accuracy of the trained model to approximately 97%. This means that quadratic and cubic SVM kernel function work very well to detect and isolate the proposed fault conditions of an induction motor. The same phenomenon is true for all the confidence matrix figures. In figure 8, the confidence matrix shows that isolating healthy data from broken rotor bar fault data has accuracy of 50% which means that the trained model is not good enough to detect and isolate faults using liner SVM kernel function.

Figure 6: Confidence matrix of SVM trained model of current data at Linear, Quadratic, Cubic, Medium gaussian and Coarse gaussian SVM kernel functions

Figure 7:Confidence matrix of SVM trained model of current data at Fine gaussian SVM kernel function

Figure 8:Confidence matrix of SVM trained model of vibration data at Linear SVM kernel function

Figure 9:Confidence matrix of SVM trained model of vibration data at Quadratic & Cubic SVM kernel functions

Figure 10:Confidence matrix of SVM trained model of vibration data at Fine Gaussian & Coarse Gaussian SVM kernel functions

Figure 11:Confidence matrix of SVM trained model of vibration data at medium gaussian SVM kernel functions

Chapter 6 Conclusions and future work

- In this project, offline data is used to train the model to detect the fault.
- Quadratic and Cubic SVM for both current and vibration have training accuracy above 85%. Therefore, they are considered to be best fitted for fault classification using both mechanical and electrical fault of the induction motor. However, if the only electrical data signal is used such as current data, any kernel function of SVM except fine gaussian SVM can be used.
- Processing the raw data prior SVM model training is essential to achieve precise training and accuracy of fault detection using the trained SVM model.
- Future work can be implementing the same methodology to perform online testing. As illustrated in figure 12, methodology can be applied to perform online testing

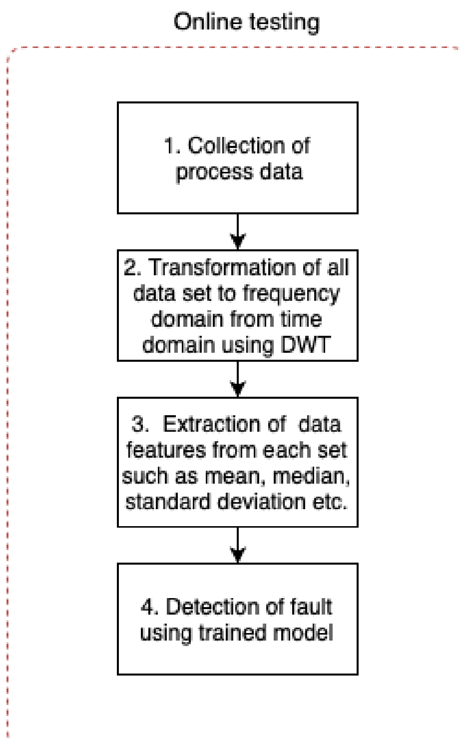

Figure 12: Online testing of data as a future work

Chapter 7 Statement of contribution

Tasks performed: The different task of the project has been divided among the group members equally as shown in Table 5.

Table 5: Implemented work plan

<table>
<tr><td rowspan="3">Work Plan</td><td colspan="5">Duration</td></tr>
<tr><td>2 Weeks</td><td>1 week</td><td>2 weeks</td><td>2 weeks</td><td>August 8, 2019</td></tr>
<tr><td>Literature review & project analysis</td><td>Modeling</td><td>Simulations & result analysis</td><td>Report writing & editing</td><td>Final report submission</td></tr>
<tr><td>Group members</td><td colspan="5">Abdullah Sifat and Zaid Kamil</td></tr>
</table>

Abdullah Sifat **Mohammad Zaid Kamil**

Signature Signature

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Appendix

MATLAB application used: Wavelet Analyzer, Classification Learner

Code:

```
clear all
clc
load ('current_BF.mat');
load ('current_BRB.mat');
load ('current_H.mat');
load ('vibration_BF.mat');
load ('vibration_BRB.mat');
load ('vibration_H.mat');
% I_BF
n = length(I_BF) / 10 ;
st = 1 ;
stp = n ;
A = zeros(n,10) ;
for i = 1:10
    A(:,i) = I_BF (st:stp) ;
    st = st + n ;
    stp = st + n - 1 ;
end
IBF01 = A(:,1) ;
IBF02 = A(:,2) ;
IBF03 = A(:,3) ;
IBF04 = A(:,4) ;
IBF05 = A(:,5) ;
IBF06 = A(:,6) ;
IBF07 = A(:,7) ;
IBF08 = A(:,8) ;
IBF09 = A(:,9) ;
IBF10 = A(:,10) ;
% I_BRB
n = length(I_BRB) / 10 ;
st = 1 ;
stp = n ;
B = zeros(n,10) ;
for i = 1:10
    B(:,i) = I_BRB (st:stp) ;
    st = st + n ;
    stp = st + n - 1 ;
end
IBRB01 = B(:,1) ;
IBRB02 = B(:,2) ;
IBRB03 = B(:,3) ;
IBRB04 = B(:,4) ;
IBRB05 = B(:,5) ;
IBRB06 = B(:,6) ;
IBRB07 = B(:,7) ;
IBRB08 = B(:,8) ;
IBRB09 = B(:,9) ;
IBRB10 = B(:,10) ;
% I_H
n = length(I_H) / 10 ;
```

```
st = 1 ;
stp = n ;
C = zeros(n,10) ;
for i = 1:10
    C(:,i) = I_H (st:stp) ;
    st = st + n ;
    stp = st + n - 1 ;
end
IH01 = C(:,1) ;
IH02 = C(:,2) ;
IH03 = C(:,3) ;
IH04 = C(:,4) ;
IH05 = C(:,5) ;
IH06 = C(:,6) ;
IH07 = C(:,7) ;
IH08 = C(:,8) ;
IH09 = C(:,9) ;
IH10 = C(:,10) ;
% V_H
n = length(vib_H) / 10 ;
VH01 = vib_H(1:n,3) ;
VH02 = vib_H(n+1:2*n,3) ;
VH03 = vib_H(2*n+1:3*n,3) ;
VH04 = vib_H(3*n+1:4*n,3) ;
VH05 = vib_H(4*n+1:5*n,3) ;
VH06 = vib_H(5*n+1:6*n,3) ;
VH07 = vib_H(6*n+1:7*n,3) ;
VH08 = vib_H(7*n+1:8*n,3) ;
VH09 = vib_H(8*n+1:9*n,3) ;
VH10 = vib_H(9*n+1:10*n,3) ;
% V_BRB
n = length(vib_BRB) / 10 ;
VBRB01 = vib_BRB(1:n,3) ;
VBRB02 = vib_BRB(n+1:2*n,3) ;
VBRB03 = vib_BRB(2*n+1:3*n,3) ;
VBRB04 = vib_BRB(3*n+1:4*n,3) ;
VBRB05 = vib_BRB(4*n+1:5*n,3) ;
VBRB06 = vib_BRB(5*n+1:6*n,3) ;
VBRB07 = vib_BRB(6*n+1:7*n,3) ;
VBRB08 = vib_BRB(7*n+1:8*n,3) ;
VBRB09 = vib_BRB(8*n+1:9*n,3) ;
VBRB10 = vib_BRB(9*n+1:10*n,3) ;
% V_BF
n = length(vib_BF) / 10 ;
VBF01 = vib_BF(1:n,3) ;
VFB02 = vib_BF(n+1:2*n,3) ;
VBF03 = vib_BF(2*n+1:3*n,3) ;
VBF04 = vib_BF(3*n+1:4*n,3) ;
VBF05 = vib_BF(4*n+1:5*n,3) ;
VBF06 = vib_BF(5*n+1:6*n,3) ;
VBF07 = vib_BF(6*n+1:7*n,3) ;
VBF08 = vib_BF(7*n+1:8*n,3) ;
VBF09 = vib_BF(8*n+1:9*n,3) ;
VBF10 = vib_BF(9*n+1:10*n,3) ;
clear A B C D E F i I_BF I_BRB I_H vib_BF vib_BRB vib_H stp st n
```