Various and multilevel of coiflet discrete wavelet transform and quadratic discriminant analysis for classification misalignment on three phase induction motor

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Abstract. For a long time ago, induction motor has been used in various industry due to strong construction, high efficiency, and cheap maintenance. Induction motor needs to be maintained regularly so that it can operate for a long time. Based on studied, bearing faults result in failure of 42% - 50% of all motor failures. One of the causes of bearing failure is misalignment when installing induction motor. This research proposes classification misalignment in induction using coiflet discrete wavelet transform and Quadratic Discriminant Analysis. Simulation of motor condition is introduced in this research as normal operation and two misalignment variations. And then, various type of coiflet discrete wavelet transform in first level until third level is used to extract motor vibration signal into high frequency signal. Then, three types of signal extraction, namely sum, range and energy level, will be used for input to Linear and Quadratic Discriminant Analysis. Linear and Quadratic Discriminant Analysis will analysis signal extraction and classify them into normal operation and two misalignment condition. The results show that first level of coiflet discrete wavelet transform is the best level for classification misalignment on induction motor, both using the Linear Discriminant Analysis and Quadratic Discriminant Analysis methods. The accuracy obtained from the two methods is the same or almost the same.

1. Introduction
For a long time ago, induction motor has been used in various industry due to strong construction, high efficiency, and inexpensive maintenance. The motors are placed in various environments and conditions that can cause damage to the motor parts. Induction motor needs to be maintained regularly so that it can operate for a long time. Most of common damage of induction motor part is bearing and winding insulation. Bearing faults result in failure of 42% - 50% of all motor failures [1-5]. Cost of bearing of motors about 3% -10% of all motor cost, but the hidden costs because of downtime and lost production can make bearing failure more and more expensive. One of cause bearing failure is misalignment of motor.

Misalignment is a condition where there is a deviation in the motor shaft with a clutch. the misalignment causes acceleration of clutch damage, bearing and produces excessive vibration [6]. The past method is using fast fourier transform (FFT) to get signal frequency of vibration. But, it just identify motor condition in normal operation or misalignment occurred.
This research proposes classification misalignment in induction using coiflet discrete wavelet transform and Quadratic Discriminant Analysis. Simulation of motor condition is introduced in this research as normal operation and two misalignment variations. And then, coiflet discrete wavelet transform in first level until third level is used to extract motor vibration signal into high frequency signal. Then, signal extraction gotten from high frequency signal is taken to analysis motor condition. Quadratic Discriminant Analysis will analysis signal extraction and classify them into three condition of motor.

2. Experimental Setup and Study Case
Laboratory experiments were carried out in this study, which consisted of an induction motor with 0.5HP power, 1400 rpm, 220 volts, 50Hz and generators as mechanical loads. To test for misalignment errors, three induction motor conditions was investigated, namely normal operation, 1mm and 1.5mm motor misalignment. Then the piezoelectric sensor was used for vibration measurement, and saved it to the SD card with the help of a microcontroller.

3. Discrete Wavelet Transform
Discrete wavelet transform (DWT) is presented in this research because it has simple calculation and relatively small time interval continuous wavelet transform. Other name of dilatation/scaling parameter is LowPass Filter (LPF) or it also can be called as father wavelet and Other name of translation parameter is High Pass Filter (HPF) or it also can be called as mother wavelet [7-9]. Both of this parameter is used if we will do wavelet transform and inverse wavelet transform. HPF and LPF filter with different cut off frequency is used to transform signal. High frequency signal or detail signal is output from HPF and low frequency signal or approximation signal is output from LPF. The relationship between HPF / mother wavelet and LPF / father wavelet can be described as in the following equation (1) and (2):

\[ \Psi(t) = \Phi(2t) - \Phi(2t-1) \]  

With \( \Psi(t) \) is the mother wavelet and \( \Phi(2t) \) is the father wavelet. The function of the equation of the father wavelet is

\[ \Phi_{j,k} = 2^{j/2}\Phi(2^j t - k), j, k \in \mathbb{Z} \]  

From equation (1) the mother wavelet and equation (2) of the father wavelet finally form the complete wavelet transformation equation, as described equation (3) below

\[ f(t) = C_{0,0}\phi(t) + \sum_{j=0}^{M-1} \sum_{k=0}^{2^j-1} d_{j,k}\Psi_{j,k}(t) \]  

Firstly, original signal is passed away in LPF and HPF filter. Then, it will be produced approximation signal (cA) and detail signal (cD) whose length is a half of sampling/ frequency of original signal. This analysis is called first level of decomposition. Then, output of LPF, called approximation signal, is used to the next level of decomposition. And we will use output of HPF, called detail signal, to processing and analysis. This decomposition process is repeated until desired level of decomposition as seen in Figure 1. Combination of the last of approximation and detail signal is called wavelet coefficient, contained information of transformation result signal compressed.

![Figure 1. Third level of decomposition](image-url)
4. Quadratic Discriminant Analysis

Quadratic Discriminant Analysis is a statistical method for classifying a number of objects into groups based on several variables, so that each object becomes a member of one group and no object becomes a member of more than one group [10]. Discriminant analysis is similar to multiple linear regression (multivariable regression). The difference is that multiple linear regression is used when the dependent variable uses a metric scale (interval and ratio) and the independent variable can be either metric or non-metric. Whereas, discriminant analysis is used if the dependent variable is categorical (using ordinal or nominal scale) and the independent variable uses a metric scale.

The discriminant analysis model is an equation that shows a linear combination of various independent variables, namely:

\[ D = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \ldots + b_kX_k \]  

(4)

Based on the equation (4) above, D is the discriminant score, b is the discrimination coefficient or weight and X is the predictor or independent variable. The estimated constants are the coefficients of b, so the value of D for each group may be different. This occurs when the ratio of the number of squares between groups to the number of squares in the group for the discriminant score reaches the maximum. Based on the D value, the value of a member is predicted.

In Quadratic Discriminant Analysis, the combination of predictor variables forms an area in the form of a graph of quadratic functions so that ordinary discriminant analysis can be corrected to produce higher accuracy. However, if the number of predictor variables is large enough, this analysis will experience overfits (variability is too large) [11].

The classification of an object into a particular population is based on a quadratic discriminant score which is formulated (5) and (6) as follows:

\[ \hat{d}^Q_1(x) = -\frac{1}{2} \ln |S| \left( -\frac{1}{2} (x - \bar{x})^T S^{-1} (x - \bar{x}) + \ln p \right) \]  

(5)

\[ \hat{d}^Q_2(x) = \max \{ \hat{d}^Q_1(x), \hat{d}^Q_2(x), \ldots, \hat{d}^Q_g(x) \} \]  

(6)

Allocate the value of the x variable to the population if and only if:

\[ S_{\text{pooled}} = \frac{n_1^{-1}S_1 + \ldots + n_g^{-1}S_g}{n_1 + \ldots + n_g} \]

5. Feature Extraction

After the discrete wavelet transforms from the motor vibration signal, then we will look for the characteristics of the detail signal or high-frequency signal from the wavelet transform. The signal detail taken is first level until third. The discrete wavelet transforms performed are coiflet discrete wavelet transform. The type of signal characteristics to be taken is the range, sum and energy. Range means that searched for its range from minimum and maximum of signal. Range of signal can be formulated as (7):

\[ \text{Range} = \text{Max of signal} - \text{min of signal} \]  

(7)

Then, sum of signal is absorbs the signal value and then adds up. Range of signal can be formulated as (8)

\[ \text{Sum} = \sum_{n=1}^{n+k} |d(n)| \]  

(8)

Meanwhile, the signal energy level is calculated by squaring each component of the signal, then summed according to the equation (9) [7,8,9]:
The result of taking characteristic extraction of the signal, will then be analyzed to determine the difference between normal motor and misalignment motor. It is also expected that the level / severity of misalignment that occurs can also be identified.

6. Analysis And Discussion
The experimental motor is then operated within a certain period of time. The result of motor vibration will be captured by the sensor and will then be stored and processed according to the system to be applied. The results of data retrieval from normal motors and motors having misalignment 1mm and 1.5mm are as shown in the Figure 2.

$$e = \sum_{n=1}^{n=k} (d(n))^2$$  \hspace{1cm} (9)

6.1. Discrete Wavelet Transform
Furthermore, motor vibration data will be transformed using coiflet discrete wavelet transform. The result of the transformed data is the detail signal at first level to the third level. The higher the level, the expected identification process will be easier. Sample of signal transformed at first level to third level can be seen in Figure 3-4.

The curve above is the result of the discrete wavelet transform of coiflet 1 from first level to third level. The type of coiflet used in this research is coiflet 1 until coiflet 5. So, each data will be transform with coiflet 1 until coiflet 5 and then will be filtered from first level to third level.
higher the level of wavelet transform used, the less data is generated as it is divided by approximation signals or low frequency signals. The data above looks cannot be used for the identification process because it is still random and looks the same between the first to third level on normal motor data and motor that experienced misalignment. So feature extraction must be applied to extract some special features of signal.

6.2. Feature Extraction

Detailed signals at first level to third level obtained from the transformation of coiflet 1 to coiflet 5 discrete wavelet transform will be extracted. Patterns or feature extraction to be taken are range, sum and signal energy level. The sample of results of the signal characteristics can be seen in table 1-2.

| Coiflet  | Level 1 | Level 2 | Level 3 |
|----------|---------|---------|---------|
| Sum      | Range   | Energy  | Sum      | Range   | Energy  | Sum      | Range   | Energy  |
| Normal   | 0.2075  | 0.0223  | 0.0117  | 0.1057  | 0.0151  | 0.0005  | 0.0801  | 0.0171  | 0.0004  |
|          | 0.1360  | 0.0177  | 0.0009  | 0.1060  | 0.0231  | 0.0008  | 0.0549  | 0.0130  | 0.0002  |
|          | 0.1740  | 0.0204  | 0.0014  | 0.0730  | 0.0143  | 0.0004  | 0.0653  | 0.0204  | 0.0004  |
| 1mm      | 0.4992  | 0.0225  | 0.0034  | 0.3519  | 0.0271  | 0.0030  | 0.1975  | 0.0266  | 0.0017  |
|          | 0.6477  | 0.0272  | 0.0049  | 0.3724  | 0.0276  | 0.0032  | 0.1354  | 0.0278  | 0.0011  |
|          | 0.5559  | 0.0223  | 0.0037  | 0.4336  | 0.0270  | 0.0040  | 0.1772  | 0.0268  | 0.0014  |
| 1.5mm    | 0.6442  | 0.0496  | 0.0065  | 0.3493  | 0.0487  | 0.0036  | 0.1886  | 0.0241  | 0.0015  |
|          | 0.6534  | 0.0752  | 0.0085  | 0.3737  | 0.0346  | 0.0037  | 0.2372  | 0.0499  | 0.0032  |
|          | 0.6133  | 0.0816  | 0.0096  | 0.3455  | 0.0467  | 0.0035  | 0.1839  | 0.0394  | 0.0020  |

If the misalignment gets bigger, the vibration of the motor will increase. The feature extraction of results of discrete wavelet transform must show an increase in value between the normal motor and the misalignment motor. In addition, motors with a high misalignment rate will show higher feature extraction results compared to motors with low misalignment.

6.3. Result Of Quadratic Discriminant Analysis

Data used as input for Quadratic Discriminant Analysis amounted to 12 training data for each normal motor condition, 1mm of misalignment and 1.5mm of misalignment. So that the total training data is 36 data. Meanwhile, the data for testing are 8 data for each normal motor condition, 1mm of misalignment and 1.5mm of misalignment. So, the total test data is 24 data. In this study, the results of Quadratic Discriminant Analysis (QDA) will be compared with Linear Discriminant Analysis (LDA) to find out the most suitable method for motor misalignment cases. In this study, Matlab software will be used to perform Quadratic Discriminant Analysis and linear discriminant analysis. The results can be seen in the Table 2 below.

| Coiflet  | Level 1 | Level 2 | Level 3 |
|----------|---------|---------|---------|
|          | LDA(%)  | QDA(%)  | LDA(%)  | QDA(%)  | LDA(%)  | QDA(%)  |
| Error of Coiflet 1 | 4.17    | 4.17    | 8.33    | 4.17    | 25      | 16.67   |
| Error of Coiflet 2 | 4.17    | 4.17    | 8.33    | 4.17    | 20.83   | 33.33   |
| Error of Coiflet 3 | 4.17    | 4.17    | 8.33    | 0       | 25      | 29.17   |
| Error of Coiflet 4 | 4.17    | 4.17    | 4.17    | 8.33    | 25      | 33.33   |
| Error of Coiflet 5 | 0       | 4.17    | 4.17    | 0       | 25      | 25      |
The table above shows that cases of motor misalignment can be classified more accurately using the Coiflet Discrete Wavelet Transform at the first level. At the second and third levels, both in Quadratic Discriminant Analysis and linear discriminant analysis, the results of the errors obtained from the classification process have a greater value than the Coiflet Discrete Wavelet Transform at the first level. Whereas, the type of Coiflet Discrete Wavelet Transform used, namely coiflet 1 to coiflet 5 does not show significant differences or even produces almost the same error. Besides that, Linear and Quadratic Discriminant Analysis in first level of Coiflet Discrete Wavelet Transform must be equally accurate in classifying each case of motor condition. It can be seen that error of classification result between Linear and Quadratic Discriminant Analysis is both around 4.17%. And besides that, Quadratic Discriminant Analysis produces classification error of 0% in second level Coiflet 3 and 5. Then, Linear Discriminant Analysis produces classification error of 0% in first level Coiflet 5. This means that each method produces the best accuracy on certain types and levels of Coiflet Discrete Wavelet Transform. So that the accuracy of each method can be said to be the same or almost the same in the case of misalignment on induction motor.

7. Conclusion
This research concerns classify misalignment in induction motor with various kind of Coiflet Discrete Wavelet Transform, multilevel of Coiflet Discrete Wavelet Transform and Discriminant Analysis. The result shows that various kind of Coiflet Discrete Wavelet Transform produces an error value that is not too much different, even almost the same. However, first level of Coiflet Discrete Wavelet Transform is the best level to extract feature extraction of signal vibration of induction motor so resulting in a low classification error. Then, Linear and Quadratic Discriminant Analysis have the same or almost the same accuracy.

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