Electrical Motor Current Signal Analysis using a Dynamic Time Warping Method for Fault Diagnosis

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Abstract. This paper presents the analysis of phase current signals to identify and quantify common faults from an electrical motor based on dynamic time warping (DTW) algorithm. In condition monitoring, measurements are often taken when the motor undertakes varying loads and speeds. The signals acquired in these conditions show similar profiles but have phase shifts, which do not line up in the time-axis for adequate comparison to discriminate the small changes in machine health conditions. In this study, DTW algorithms are exploited to align the signals to an ideal current signal constructed based on average operating conditions. In this way, comparisons between the signals can be made directly in the time domain to obtain residual signals. These residual signals are then based on to extract features for detecting and diagnosing the faults of the motor and components operating under different loads and speeds. This study provides a novel approach to the analysis of electrical current signal for diagnosis of motor faults. Experimental data sets of electrical motor current signals have been studied using DTW algorithms. Results show that DTW based residual signals highlights more the modulations due to the compressor process. And hence can obtain better fault detection and diagnosis results.

1. Introduction
With growing interest in condition monitoring, more and more advanced techniques are being introduced to detect and diagnose faults in machines more accurately\textsuperscript{[1]}. Various types of signals, such as vibration signal, acoustic signal and temperature signal, are popularly used in monitoring the conditions of a machine or process. Especially, electrical motor current signals have also been explored widely to analyse the health of the induction machine for decades\textsuperscript{[2]} due to that the method needs less cost in supply measurement system and can be implemented remotely. In terms of signal processing, numerous novel signal processing techniques are employed to analyse the data for improving the accuracy of the fault diagnosis. These researches have made significant progress in predictive condition monitoring and fault detection algorithms.

The basic approaches used for fault detection are based on the comparison of correlate numerical models with measured modal properties from undamaged and damaged components. Measurements are normally made in the time domain while a machine runs under different loads and speeds. Then
the signals acquired in the test are analyzed in the time and frequency domains based on various signal processing techniques for extracting diagnostic features which can be compared accurately. However, feature extraction can be degraded by many factors. One of them is that the random noise from test facilities or the around environment contaminates monitoring signals. It not only influences the accuracy of feature extraction but also increases the complexity of the extraction process. Another factor is that monitoring signals obtained often show similar profiles but have dynamic phase shift due to speed variation, making it not possible to compare between signals collected in different times and different operating conditions. Therefore, detection features derived directly in the time domain are often not accurate enough to discriminate small changes from machine healthy conditions.

The influences of the random noise could be reduced by averaging the monitoring signals or using filter techniques to obtain the signals including interesting frequency. Numerous signal processing techniques are also used for signal preprocessing in order to improve the accuracy of fault diagnosis, such as time domain average synchronous (TDAS), frequency domain average synchronous (FDAS) and wavelet denoise. Particularly, TDAS shows more effective in noise reduction and produces better diagnosis, which indicates that time domain based methods deserve more study for more accurate diagnosis.

Therefore, this paper focuses on extracting short transient events inside electrical current signals by a signal phase alignment scheme. A Dynamic Time Warping Algorithm (DTW), a time domain method, is explored to align the signals in order to undo the changes. First of all, the classic DTW algorithms are reviewed, and then the method of improving the computing time of DTW algorithm is explored based on both the simulated and experimental data. Finally, the electrical current signals obtained under different conditions are analysed for compressor faults detection after preprocessing the signals by DTW algorithms.

2. Classic Dynamic Time Warping

Dynamic Time Warping (DTW) is an algorithm for aligning two time series which are similar, but out of synchronization and generally not of exactly the same length[3]. It aligns two time series through measuring and minimizing the distance between each point of the two series sequences. The Euclidean distance is the simplest and commonly used in distance measurement[4]. Therefore, the minimum distance warping path can be obtained by optimizing the distance measurement subject to several constrains[5]. Because it is allowed to assign multiple successive values of one time series to a single value in the other time series, DTW can be employed to process the series sequences of different lengths.

DTW uses dynamic programming to search a distance of mapping between the time axes of two series sequences to find the minimum distance between them. Generally, certain constraints are utilized on DTW to optimize the search of the warping path. As an effective method to characterize the similarity of two time series, DTW has been widely used in various application domains[3], such as speech recognition, “data mining”, and the recognition of on-line signatures, handwritten signatures captured by means of a graphic tablet or a special pen in the form of time series for the pen position. Suppose there are two time series A and B[5, 6],

\[ A = (a_i) \quad i = 1, ..., m \]
\[ B = (b_j) \quad j = 1, ..., n \]

\[ \text{.........} \quad (1) \]

The two time series of length are m and n respectively. Let distance \( d(a_i, b_j) \) be a point-to-point distance between \( a_i \) and \( b_j \). The point-to-point distance between \( a_i \) and \( b_j \) can be defined in different ways[3], e.g. as the Euclidean distance or as the absolute value norm of the difference vector of \( a_i \) and \( b_j \). To align two sequences using DTW an n-by-m matrix M contains the distance \( d(a_i, b_j) \) between the two points \( a_i \) and \( b_j \). Each matrix index \((i, j)\) corresponds to the alignment between the points \( a_i \) and \( b_j \).
A warp path $W = w_1, w_2, ..., w_k$, is a sequence of grid points, where each $w_k$ corresponds to point $(i, j)_k$. Warp path $W$ maps the elements of sequences $A$ and $B$ as illustrated in Figure 1(b). From the warping path, it can be seen that the warping path coincides with the diagonal line when there is no differences in the start portion, middle portion and the end portion between the two sequences. However, other portions of the signals have large differences and the warping path deviates more from the diagonal line.

To implement DTW, the constrains of a warping path[5] includes:

1. Boundary conditions: $w_1 = (1, 1)$ and $w_k = (i, j)$;
2. Continuity: Given $w_k = (a, b)$ then $w_{k-1} = (a', b')$ where $a - a' \leq 1$ and $b - b' \leq 1$; and
3. Monotonicity: Given $w_k = (a, b)$ then $w_{k-1} = (a', b')$ where $a - a' \geq 0$ and $b - b' \geq 0$.

These constrains determine the warping path to start in the first point and end in the last point for both sequences and the allowable steps are restricted in the warping path to adjacent points. In addition, the points in warping path must be monotonically spaced in time.

The accumulated distance $d_W(A, B)$ between $A$ and $B$ for a given warping path $W$ is the sum of point-to-point distance of distance $(a_i, b_j)$ along the warping path[5], the Euclidean distance are used to calculate the distance:

$$d_W(A, B) = \sum_{(i,j)\in W} \text{distance}(a_i, b_j)$$  \hspace{1cm} \text{(2)}

The goal is to determine a warping path for which the accumulated distance between $A$ and $B$ is minimal:

$$d(A, B) = \min_{W\in \mathbb{W}} d_W(A, B)$$ \hspace{1cm} \text{(3)}

This is the optimal warping path. The minimal distance between $A$ and $B$ quantifies the dissimilarity of $A$ and $B$. Usually, the optimal path is acquired by dynamic programming. Dynamic programming is a time-consuming procedure. The computing time is reduced by looking for the optimal distortion path only within a limited band.

The warping path can be found more efficiently using a dynamic programming. It evaluates the following recurrence which defines the cumulative distance $\gamma(i, j)$ as the distance $d(i, j)$ found in the current cell. The minimum of the cumulative distances of the adjacent elements is [7, 8]

$$\gamma(i, j) = d(a_i, b_j) + \min \{ \gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1) \}$$

Where

$$d(a_i, b_j) = (a_i - b_j)^2$$ \hspace{1cm} \text{(4)}

The distance corresponding to the minimal distance warp path equals the value in the cell of the matrix $M$ with the highest indexes $M(n, m)$. A minimal distance warp path can be obtained by following cells with the smallest values from $M(1, 1)$ to $M(n, m)$.

Two data sequences with similar profiles but different lengths are illustrated in Figure 1 (a). DTW algorithms are employed to the two sequences. The warp path starts at point $(1,1)$ and ends at points$(i, j)$. It is optimized through minimizing the accumulated distance to find the warping path as
shown in Figure 1(b). The marker points in Figure 1(b) are the optimal warping path for the two sequences. Figure 1 (c) indicates the aligned series sequences by DTW according to the optimized warping path. It is clear that the two series sequences are matched in accordance with the time-axis.

3. Optimization of Dynamic Time Warping

One of disadvantages using the classic Dynamic Time Warping algorithm is the high demand of computational power. It is limit to process the large datasets. Because of the shortcoming of DTW algorithm, various modifications are suggested[9]. However, it is difficult to improve the time-consuming of DTW because it is based on the principle of accumulative. DTW algorithms carry out based on calculating the distance between each point from the reference time sequence to each point from the misaligned sequence and then accumulate the distances to obtain the entire set of distances before retrieving them to look for the minimum warping path[9]. This process determines that the warping path cannot extract until the partial accumulation is available for consideration. The partial accumulation is the main time consumes process in DTW algorithm. According to this condition mentioned above, all the approaches explored to speed up the distance calculations are approximation.

The dimensionality reduction technique is one of the popular approximation methods that explored for speeding up the DTW algorithms. It is a modification of DTW that performs warping on the reduced dimensionality representation of the signal[10]. The original data sequence is divided into equal length segments and then the mean value of data points in each segment is calculated to generate a new series sequence. Figure 2 is an example of the dimensionality reduction. The original data sequences are divided using the length of segments is 10 points and then the mean value of each 10 points is calculated as one point in the reduced dimensionality. Figure 2(a) illustrated the original misaligned signals and figure 2(b) shows the piecewise signals after the dimensionality reduction by a factor 10. It is demonstrated that the segmental signals can keep basic characteristics of the original signals even after the dimensionality reduction.
The intuition of the warping path modification is shown in Figure 3. It shows warping path of the segmental data sequences after the dimensionality reduction. Figure 4 shows the alignment of the two data sequences after dimensionality reduction. It can be seen that the main two significant phase shifts happening around sample 40 and 115 respectively, which are also indicated in the warping data.

In this simulation, the CPU time used for aligning the original signals is 2.607 seconds whereas the time for aligning the segmental signals is only 1.229 seconds, less than 50% of the original time. The simulation was tested in a computer with configuration of Intel (R) Core (TM) 2 Duo CPU P8700 @ 2.53GHz, 2GB memory.

4. Experimental Evaluation

4.1. Electrical Motor Current Signals

The experiment is operated on a two-stage reciprocating compressor test rigs, electrical motor current signals of a two-stage reciprocating compressor are acquired to identify and quantify common faults of the compressor. For the previous research inf[11], it demonstrated that the influence of mechanical problems that result in rotor disturbances can be detected through the changes in the induction machine stator current signals, and the induction machine stator current can be used to detect the presence of load imbalance [12].

In the experiment, the compressor is running under different load conditions with various types of faults, including valve leakage, inter-cooler leakage and belt looseness. In addition, the compressor
electrical current signal under health conditions is obtained in advance used as a baseline for the comparison. Figure 5 illustrates the electrical current signal of the test rigs. It shows that the signal consists of mainly a 50Hz component but modulated by compressor working frequency 7.3Hz. The features of the modulation under different conditions can be extracted for faults detection.

4.2. Faults Analysis and Results Discussion
In feature extraction for faults analysis[13], an artificial reference current signal with a frequency of 50Hz is employed to compare with the experimental signals. The amplitude of the reference current signal is equal to the peak value of the experimental signal at 50Hz. Using DTW a residual signal can be obtained by subtracting the reference from the measured signal, which removes the 50Hz component and leaves only that due to the modulation for more accurate comparison.

In the time domain, as shown in Figure 6 (a), the reference and experimental electrical current signals are not lined up and as such, the waveform subtraction cannot be done directly in the time domain. The DTW algorithm is explored to align the two signals and dimensionality reduction technique is used for run-time savings of DTW algorithm. Figure 6(b) shows the alignment after DTW processing and it is clear that the two signals match each other very well after processing. Therefore a comparison can be made by subtracting the two signals in Figure 6(b) directly. The time domain residual signal and its spectrum are illustrated in Figure 7. It can be seen that the residual signal after processed by DTW do not lose information and the frequency components due to the operation process of the
compressor are clear according to Figure 7(b). Therefore, the residual signals can be used to obtain a
more accurate detection feature.

![Residual Electrical Current Signal](image1)

![Spectrum of Residual Electrical Current Signal](image2)

Figure 7. The residual signal in the time and

![The RMS Values from Envelope Analysis and DTW](image3)

![Normalised RMS Values from Envelope Analysis and DTW](image4)

Figure 8. Diagnosis performance of DTW and

Envelope analysis

The root mean squared values (RMS) of residual signals are calculated for different healthy cases of
the compressor as shown in Figure 8. The comparison of the RMS values from envelope and DTW
analysis is shown in Figure 8(a). The normalized amplitudes of RMS values for compressor operating
under different conditions analysed by envelope analysis and DTW respectively, as shown in Figure
8(b). It can be seen that the DTW highlights more the changes from the baseline under different
conditions, showing that DTW outperforms the conventional envelop analysis in differentiating the
faults from each other and from the healthy case. In addition, the fault differentiation has been
evaluated in both low and high discharge pressures.

5. Conclusion

In this paper, the Dynamic Time Warping algorithm is used for aligning electrical current signals for
compressor faults diagnosis. Moreover, a dimensionality reduction technique is explored to speed up
the DTW algorithm and hence to increase the data size to be processed. Both simulation and
experimental data are employed to test the performance of the optimized DTW algorithm. The results
demonstrated that the DTW algorithm is suitable to align signals that have similar profiles but misaligned in time-axis and the run-time of the algorithm is improved significantly through the
dimensionality reduction technique. The fault detection results show that the DTW allows aligning
dynamic signals acquired at different time when a machine is operating under different process
conditions. The direct comparison of the aligned signals in the time domain produces better diagnostic
results compared with that from envelope signals obtained using FFT.

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