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Research Article

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Time-domain signal feature extraction of mechanical and electrical equipment based on improved dynamic time warping

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ABSTRACT

This paper proposed a new method of time-domain signal feature extraction and fault diagnostic based on improved dynamic time warping method of mechanical and electrical equipment. Dynamic time warping method was improved by integrating the methods of phase compensation, weighted gradient, derivatives, sliding window connection, fast dynamic time planning. Then improved dynamic time warping method may be applied directly to extract the signals of domain statistical parameters of fault feature of mechanical and electrical equipments and get accurate residual signal sequence with fault sideband features. Identification and localization of fault signal features may be done by selecting peak value, RMS, kurtosis and other statistical characteristics identify and detect faults. Using new statistical parameter Thikat to forecast failure trend is a new method of fault detection and diagnosis of electromechanical equipments.

Key words: Time-domain; Dynamic time warping; fault diagnosis; trend forecast

INTRODUCTION

The key technique for feature extraction in fault detection system of mechanical and electrical equipment was feature extraction in frequency domain by Fourier transform. Although it is possible to obtain satisfactory results feature extraction, the Fourier transform based frequency domain features extraction method also has some limitations, such as aliasing^[1], spectral leakage^{[2][3]} and fence effect^{[1][4]}, etc. In particular, the latter two limitations can lead to very significant errors of spectrum estimation. And weak fault signal can not be accurately detected and diagnosed.

Direct use of the time-domain fault feature extraction technique in fault detection of planetary gearbox can avoid many shortcomings of fault feature extraction based Fourier transform in the frequency domain. Dynamic time warping used in speech recognition widely was migrated to fault feature extraction and diagnosis in time domain. Used the improved method, limitations of frequency domain processing based Fourier transform were eliminated and high cost of time-domain synchronous averaging method was avoided. It was a kind of very effective method of identification, data mining and signal processing.

There were disadvantages of large computation, computational complexity, singularity, bad robustness when dynamic time warping method was used in fault feature extraction of mechanical and electrical equipment directly. So disadvantages of dynamic time warping methods must be improved in order to get accurate time-domain signal residuals and more efficient time-domain fault feature extraction^{[5][6][7][8]}...

In the paper, a new method of time-domain signal feature extraction and fault diagnostic based on improved dynamic time warping method of mechanical and electrical equipment. And new time-domain fault trend prediction method of mechanical and electrical equipment was established based on parameter Thikat. A new idea and target

was provided for fault diagnosis of mechanical and electrical equipment.

1. Dynamic Time Warping Method

Time series are regulated nonlinearly used the method of uniform and non-uniform deformation along the time axis to stretch and contract in dynamic time warping method. And optimum match path of time calibration of characteristics signal of test pattern and reference pattern was set and the shortest distance was got. Then similar characteristics of two time series are matched and compared.

Dynamic time warping algorithm is generally divided into two steps.

First step is to calculate the distance between frames of two time series and get Euclidean distance matrix. The second is to find an optimal path in the distance matrix.

There are two time series, X and Y, respective lengths n and m,

$$X = (x_1, x_2, \dots, x_n) \tag{1}$$

$$Y = (y_1, y_2, \dots, y_n) \tag{2}$$

X sequence is measurement sequence and Y sequence is reference sequence. a Euclidean distance matrix $n \times m$ was built. Elements of matrix (i, j) were Euclidean distance $(x_i - y_j)^2$ of x_i and y_j .

Warping path function W was Build, k-th element of W was defined as $w_k=(i, j)_k$. So

$$W = w_1, w_2, \dots, w_k \max(m, n) \le K \le m + n + 1$$
 (3)

Warping path W must meet following constraints:

- (1) Boundary constraint: $w_1=(1, 1)$ and $w_K=(n, m)$. Starting and end point of warping path must be the first point of the regular time series and the last point.
- (2) Continuous constraint: if $w_k=(a, b)$, $w_{k-1}=(a', b')$, $a-a' \le 1$, $b-b' \le 1$. This limits the neighbor elements (including diagonally adjacent) in the allowed step of warping path
- (3) Monotonic constraint: If $w_k=(a, b)$, $w_{k-1}=(a', b')$, $a-a' \ge 0$, $b-b' \ge 0$. Points in warping path were limited to layout monotonically in time.

Target of dynamic warping algorithm was to find optimum wraping path with minimum cumulative of two time series. Define objective function of optimum wraping path:

$$D(X,Y) = \min_{w \in W} \sum_{(i,j) \in w} (x_i - y_j)^2$$
 (4)

$$D(i,j) = (x_i - y_j)^2 + \min((x_{i-1} - y_{j-1})^2, (x_{i-1} - y_j)^2, (x_i - y_{j-1})^2 \ i \in [1:N], \ j \in [1:M]$$
(5)

Where $D(1, j) = \sum_{k=1}^{j} c_{1k}, j \in [1:M]$

$$D(i,1) = \sum_{k=1}^{i} c_{k1}, i \in [1:N]$$

Accumulated distance was defined as minimum sum of accumulated distance between the current cell and adjacent elements.

The minimum total cumulative distance was calculated from (1, 1) to (N, M) according to equation after building the cumulative distance matrix and the best match wraping path was got. Match results of two time series used dynamic time wraping method was shown as Figure.1. Signals of two time series based on optimum path produced by dynamic programming were well matched.

2. Fault features Extraction based on improved dynamic time warping

Integration of phase compensation, slope weighted, derivative, sliding window connection, fast dynamic time planning method is applied to dynamic time warping method in order to achieve small computing amount, high precision, fast and robust of feature extraction algorithms of fault signal of mechanical and electrical equipment. And improved dynamic time warping algorithm suit to fault feature extraction of mechanical and electrical equipment was designed and integrated.

2.1 Savitzky-Golay smoothing of time series

Savitzky-Golay smoothing method of time series was applied to dynamic time warping method to filter signal,

smooth noise data, eliminating data points with large errors obstacles. And smoothness and robustness of algorithms was enhanced by direct dealment.

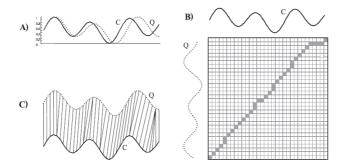


Figure.1 Matching schematic of dynamic time wraping method

The best fit was done by moving the windows used least square method based on the polynomial in the time domain. The p-th binary polynomial fit was got to value D of each point in the sliding window $l \times m$, where l and m are the window size and odd numbers. Then corresponding coefficients of polynomial were determined when fitting error was the least based the least square method. And the best-fit values of P (i, j) of center point (i, j) in $l \times m$ sliding window were got, which was the new value after de-noising processing. Sliding data window sledded sequentially along each point in the three-dimensional space and was dealt smoothly.

2.2 Phase estimation and compensation method

Phase compensation method was used to enhance smoothness and robustness and improve singularity problem of dynamic time warping signal processing for reduction of the data transitions. And the reliability and accuracy of the signals may be improved.

Generalized metric of Euclidean distance of two signal time series was got according to phase difference of test points and the reference points used method of phase estimation and compensation. The initial phase was obtained by calculating the minimum Euclidean distance matrix. And phase errors cause by singularity of reference signals and filtered signals were compensated and corrected.

2.3 Slope weighting techniques and derivative methods

Corrected logic weighting function based phase deviation was found and weight of each point in time series was allocated optimally used the methods of logic weighting function and slope weighting.

Time series data was processed to data with waveform characteristics used derivative method. And wraping matrix was found and wraping path was optimized to process feature signal used logic weighting method of dynamic time warping.

Correction logic weighting function:

$$w_{i} = \left[\frac{w_{\text{max}}}{1 + e^{-g(i - m_{c})}}\right]$$
 (6)

Where i=1, m. m is length of time series and m_c mid-point of time series.

w_{max} is maximum value of weight coefficient and g is penalty factor.

Processing method of derived weighted logic dynamic time warping:

$$WDDTW_p(D_A, D_V) = \sqrt[p]{\xi^*(i, j)}$$
 (7)

Where

 $\xi^*(i,j) = \left| w_{|i-j|} (d_i^a - d_j^b) \right|^p + \min \left| \xi^*(i-1,j-1), \xi^*(i-1,j), \xi^*(i,j-1) \right|$ Sliding window connection, fast dynamic time planning

Algorithm accuracy was improved and optimum was done integrated sliding window algorithm, fast dynamic programming algorithm to reduce calculation amount and space complexity of dynamic time warping algorithm.

Firstly new time series were created after 1/2 processing data quantity of time series signals of pretreatment. Then optimum path was established and time series signals were input after mapping original preprocessing. Finally extended mapping paths of searching sliding window were established as predefined radius. Only signal data in searching window was calculated used the algorithm. And calculation space was simplified and computing speed was improved.

Fault signal detection Band pass filtering Savitzky-Golay time series smoothing Reference signal estimation **Ouick Search window** size decision Phase estimation and compensation Improved DTW Algorithm of quick search sliding window Optimum dynamic programming algorithm of logic weights derived phase compensation Residual vector signal of fault signal

Technology Roadmap was shown as Figure.2.

Figure.2 Technology roadmap of fault feature extraction based improved dynamic time warping

3. Fault feature identification and localization based Thikat

Feature identification and localization of fault signal was done by selecting statistical characteristic parameters such as peak, RMS, kurtosis spectrum to identify and detect faulty after using improved dynamic time warping to get residual signal sequence with fault sideband feature.

SADOK SASSI and BECHIR BADRI integrated part of the statistical characteristics parameters and proposed two new statistical parameters Talaf and Thikat ^[9] in order to be able to determine the node of catastrophic accidents in bearing fault diagnosis in 2008.

Omar D. Mohammed and Matti Rantatalo had done research work characteristics and effectiveness of Talaf and

Thikat parameters in gear failures [10]. Thikat parameter was introduced to fault diagnosis of mechanical and electrical equipment. And status and trends of fault signals was predicted after feature extraction and the timing of specific maintenance evaluation was studied.

Correlation spectrum kurtosis and Thikat parameter was used to design a kind of new identification and localization algorithm of residual signal feature vector of mechanical and electrical equipment. Time-domain residual signal vector was detected, identified and located and failure size and trends were predicted used the method.

3.1 Fault location method based on correlation spectrum kurtosis analysis

The method of maximum correlation kurtosis deconvolution (MCKD) was used to filter time domain residual signal. And correlation kurtosis parameters analysis was utilized to evaluate health status to identify and locate the fault used periodic of fault signal.

Firstly the original signal timeline signal length was recovered by pre-processing and signals after processing by improved DTW were filtered used the maximum correlation kurtosis deconvolution method.

Then concerned period T was determined and X_0^T , $(X_0X_0^T)^{-1}$ of input signal is calculated after pretreatment.

Filter size was selected and the initial filter value of $\vec{f} = [00...1-1...00]^T$ was set. Filtered output signal \vec{y} was calculated and signals filtered by the maximum correlation signal kurtosis deconvolution were got ultimately.

$$MCKD_{M}(T) = \max_{\vec{f}} CK_{M}(T) = \max_{\vec{f}} \frac{\sum_{n=1}^{N} (\prod_{m=0}^{M} y_{n-mT})^{2}}{(\sum_{n=1}^{N} y_{n}^{2})^{M+1}} (8) \vec{f} = \frac{\|\vec{y}\|}{2\|\vec{\beta}\|^{2}} (X_{0} X_{0}^{T})^{-1} \sum_{m=0}^{M} X_{mT} \vec{\alpha}_{m}$$
(9)

Correlation kurtosis value was got by calculating filtered signal used correlation kurtosis analysis. Then residual vector signal was analyzed according to correlation between different fault period of different gears and rotational frequency of different gears and fault was located.

$$CK_{M}(T) = \frac{\sum_{n=1}^{N} \left(\prod_{m=0}^{M} x_{n-mT} \right)^{2}}{\left(\sum_{n=1}^{N} x_{n}^{2} \right)^{M+1}}$$

$$y_{n} = \sum_{k=1}^{L} f_{k} x_{n-k+1}, x_{n} = 0, y_{n} = 0, (n \neq 1, 2, ..., N)$$
(11)

3.2 Fault trend prediction method based Thikat

Fault size and trends were determined used Thikat evaluation method. Then maintenance methods, timing, programs and working life were got and emergency fault was alarmed.

Firstly Talaf time domain vector evaluation method was used to establish development trend curve of fault size of time-domain residual signal vector. Then running area with fault and repair replacement area were determined.

Peak values, RMS, peak factor, kurtosis were substituted into Formula (12) and Talaf was got.

$$TALAF = \log[Ku + \frac{RMS}{RMS_0}]$$
 (12)

Trend correlation curve between fault development and Talaf parameter was found according to fault format of different size of the same fault. And four regions were subdivided according to curve slope.

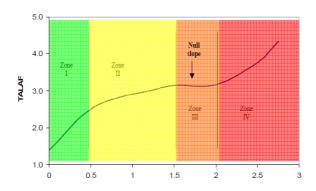


Figure.3 Map of Talaf trend curve of fault development

Thikat evaluation method of time-domain vector was used and Thikat value was monitored when fault was found. Then thresholds were set according to trend zone of fault development. Maintenance and replacements were done when alarm thresholds of time domain residual signal vector of repair replacement area were achieved.

Peak values, RMS, peak factor, kurtosis were substituted into Formula (13) and Thikat was got.

$$THIKAT = \log[(Ku)^{CF} + (\frac{RMS}{RMS_0})^{peak}]$$
 (13)

Thikat value was monitored and threshold alarm would be done when it reached red zone of Figure.4.

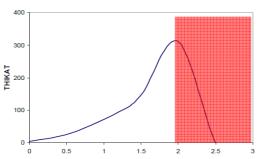
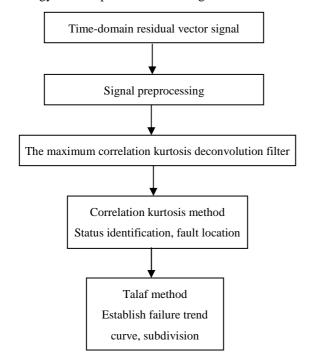


Figure.4 Map of Thikat trend curve of fault development

Technology Roadmap was shown as Figure.5.



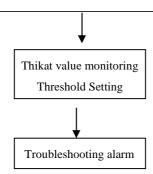


Figure.5 Identification and localization of fault feature based on Thikat

CONCLUSION

Dynamic time warping used in speech recognition widely was migrated to fault feature extraction and diagnosis in time domain. Integration of phase compensation, slope weighted, derivative, sliding window connection, fast dynamic time planning method is applied to dynamic time warping method to improve the disadvantages of large computation, computational complexity, singularity, bad robustness when it is used in fault feature extraction of mechanical and electrical equipment directly

Identification and localization of fault signal characteristics may be done by improving dynamic time warping method to obtain a residual signal sequences with fault characterized sidebands and selecting the statistical characteristic parameters such as peak, RMS, kurtosis spectrum to complete identification and localization of fault signal characteristics. New time-domain fault trend prediction method of mechanical and electrical equipment was established based on new statistical parameter Thikat. Firstly thresholds based on the development trend of the fault area were set used Thikat evaluation method of time-domain vector. Then status and trends of fault signal after feature extraction was predicted and specific repair time was decided. Then alarm was given for maintenance and replacement reached alarm thresholds of time domain residual signal vector of repair and replacement. A new idea and target was provided for fault diagnosis of mechanical and electrical equipment.

How to apply and complete improved fault diagnosis method based improved DTW in engineering practice of complex electromechanical equipments such as planetary gearboxes and rotating machinery will be the focus of future research work. Next main work is to determine parameters of filter, Threshold RMS, Thikat threshold in the study of planetary gearbox.

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