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Localization of Acoustic Emission Source Based on Chaotic Neural Networks

Aidong Deng[1], *Xiaodan Zhang*[2], *Jianeng Tang*[2], *Li Zhao*[2],*Kang Qin*[1]

[1] National Engineering Research Center of Turbo-generator Vibration, Southeast University, Nanjing 210096, China
[2] School of Information Science and Engineering, Southeast University, Nanjing 210096, China

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Abstract: Because of containing several model waveforms and transmission speed of each model are various, the source signal of rub-impact acoustic emission (AE) will lead to waveform distortion in propagation process, and it is difficult to achieve exact source location by traditional time difference of arrival algorithm. A chaotic neural network technique was introduced to calculate the location of AE source. Numerous researches show that rotor rub-impact fault has sufficient non-linear features, so obtain the characteristics of the non-linear dynamics which reveal the AE source form the rub-impact data by using the chaos theory and use it as the input of the neural network to get the localization. We propose a modified Gaussian Mixed Model (GMM) with an embedded Time Delay Neural Network (TDNN). It integrates the merits of GMM and TDNN. Simulation results prove, theoretically and practically, that it can locate AE source efficiently and provide the basis for the rotor rub-impact fault diagnosis, so it has good application prospect and is worth to research further more.

Keywords: Acoustic emission, Localization, Rub-impact, Chaos, Neural network, GMM, TDNN.

1. Introduction

Malfunction diagnosis technologies based on rotor rub-impact of AE determines the occurrence of rub-impact by AE signal, and finds the location of rub-impact by AE source location technique quickly. Using acoustic emission technology can detect the malfunctions online and in real-time, find the location of acoustic emission fast and lossless, estimate the property and risk, and so on, providing the important information to analysis the cause of malfunctions and solve them.

The common positioning method is TDOA location method[1-2], which calculates the AE source location by the time difference of different homologous signals reaching to different sensors. However, in the structure of the rotor system, the propagation path between the rub source and the sensor is often non-continuous, non-single-media and complex. During the dissemination, the signal of Multimodal AE waves inspired by rub-impact distorts seriously because of the impacts of dispersion, boundary conditions, frequency dispersion, pattern conversion and so on, coupled with the impact of instrument response, the mapping between the AE source and the signal detected by sensor is nonlinear, so it is difficult to model accurately and define the time difference, and the threshold set of emitting trigger sound event depends on the practical experience of engineering staff. Because of these factors, the exact location of rub-impact source in rotor system becomes very difficult.

In order to minimize the impacts of human factors, intelligent optimization algorithms have been widely used in the damage location. In intelligent algorithms, neural network technology, which breaks through the limitations of digital computer based on traditional linear processing has its unique characteristics and is a continuous-time dynamic system with highly nonlinear large scale. Thus is widely used in the fields of structural damage diagnosis, pattern recognition, control optimization and intelligent information processing[3-5].

When rotor rub, the vibration has obvious nonlinear characteristic related to rubbing conditions closely and uncertainty of chaotic nature[6-7]. Some scholars conduct theoretical calculation and experimental research on the malfunction of rub-impact in the use of the fractal theory,

* Corresponding author: e-mail: addseu@163.com

apply the fractal dimension to the vibration malfunction diagnosis of rotor system and achieve good results[8-10].

This paper takes account of TDNN and GMM with their respective advantages, and introduces a way of combining GMM and TDNN. It embeds TDNN into the GMM and takes maximum likelihood (ML) as the common goal of the training of GMM and TDNN. So the TDNN can be able to learn the difference between the feature vector, and the feature vector set mapping can increase the likelihood of sub-space. We propose a two-stage learning method, which alternately updates the parameters of GMM and TDNN, can inhibit the effect of invalid characteristic parameters, and enhances the role of the effective characteristic parameters.

This letter utilizes the chaotic characteristics of rubbing signal to extract the most revealing acoustic emission sources of non-linear dynamics of characteristics quantity-the correlation dimension, largest Lyapunov index and the Kolmogorov entropy. It use these as the input of neural network to generate the intelligent localization of the rubbing acoustic emission source, Experimental results show the feasibility of the positioning method.

2. Gaussian Mixed Model (GMM) with an Embedded Time Delay Neural Network (TDNN)

GMM can be seen as a HMM of one state. The probability density function of a M-order GMM is consist of weighted summation of M Gaussian probability density function, which can be expressed as[11-12]:

$$p(x_t\,|\lambda) = \sum_{i=1}^{M} p_i b_i(x_t) \tag{1}$$

The x_t here is a D-dimensional random vector, x_t describes feature vector of feature parameters in AE signal; $b_i(x_t)$,$i = 1, 2, ..., M$ are members of density; p_i,$i = 1, 2, ..., M$ are the mixing weights. Each of the members of density is the Gaussian function of both u_i as a mean vector and $\sum_i$ as a covariance matrix, which can be expressed as:

$$b_i(x_t) = \frac{1}{(2\pi)^{D/2}\left|\sum_i\right|^{1/2}} e^{[-\frac{1}{2}(x_t-u_i)^T \sum_i^{-1}(x_t-u_i)]} \tag{2}$$

Here p_i must satisfy the condition: $\sum_{i=1}^{M} p_i = 1$

Complete Gaussian mixture density is consist of the parameterized mean vectors, covariance matrixes and mixing weights of all members of density. It can be defined as follows:

$$\lambda_i = \{p_i, u_i, \textstyle\sum_i\}, i = 1, 2, ..., M \tag{3}$$

For the recognition of Rotor Collision Acoustic Emission signal, each type of Rotor Collision Acoustic Emission signal is represented by a GMM and his (her) model parameter λ_i.For the list $X = X_1, X_2, ..., X_T$ of T testing vectors, its GMM likelihood probability can be written as:

$$L(X\,|\lambda) = \log P(X\,|\lambda) = \sum_{t=1}^{T} \log p(X_t\,|\lambda) \tag{4}$$

Time Delay Neural Network (TDNN) has been widely used in pattern recognition, it has the ability to compare and associate the current input and previous input. Therefore, network input must be in accordance with the order of time sequence. There are TDNN networks with feedback and without feedback, and this paper mainly uses the network without feedback. Delayed vectors are transformed in non-linear manner, and the transform results are linearly weighted as output. The proposal of embedding TDNN into GMM is advanced based on the merits of GMM and TDNN. It takes advantage of GMM's ability to express data distribution and learning ability of TDNN to data structure. TDNN learns time information of vector sequences and balances the requirement of variable independent which is needed by maximum likelihood probability. They are trained as a whole, commonly use maximum likelihood probability.

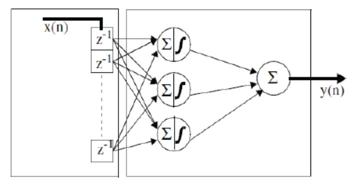


Figure 1: TDNN without feedback model

A two-stage approach is used to train the model. The process of the TDNN training and GMM training are alternating. EM method is used when training GMM. Because TDNN network is a kind of multi-layer Perceptron network (MLP), BP method with momentum is used when training TDNN.

Training process described as follows:

1. Determine the structure of GMM model and TDNN network;

2. Give convergence conditions and the largest number of iterations;

3. Select the initial parameters of TDNN network and GMM model randomly;

4. Fix the TDNN parameters, input feature vectors and get all of the residual vectors of the TDNN;

5. Use EM[11] method to modify the weights, means and variances of Gaussian distributions;

6. Fix the GMM parameters, an expression of likelihood probability will be got, then the TDNN parameters can be modified by means of BP method with momentum;

7. If the training conditions or number of iterations are satisfied, stop, or turn to 4.

Because the two-step iterative method for model parameters is adopted, in the iteration of neural network parameters, the weights, the mean vectors and variances of the Gaussian distributions are fixed.

Regardless of GMM or TDNN, the above methods are theoretically obtained point of local maxima. Therefore, it is necessary for us to train from more initial values and step sizes so that better model parameters can achieve.

3. CHAOTIC TIME SERIES ANALYSIS

Researching on chaos from the time series is dating from the theory of reconstruction of phase space put forward by Packed and so on in 1980. For the time evolution of any variable deciding the long-term evolution of system, it contains the information of long-term evolution of all variables, so we can study the chaotic behavior by a single variable time series which decides the long-term evolution of system. The constants of attractors including correlation dimension, Kolmogorov entropy and Lyapunov exponent, have been playing an important role in charactering the chaotic nature.

3.1. Phase Space Reconstruction

Phase space reconstruction was first introduced, aiming at restoring the chaotic attractor in the high-dimensional phase space. Takens have proved that a suitable embedding dimension m can be found, if $\mathrm{m} > 2\mathrm{d}+1$ (d is the dimension of dynamical system), then the regular track can be recovered in the embedding dimension space. So the selections of the time delay and the embedding dimension have great significance in the Phase Space Reconstruction.

Autocorrelation function method is a very mature way to solve the time delay[13-16], and it's mainly used to extract the linear correlation between the sequences. In general, for the chaotic time series, it needs to calculate its autocorrelation function first and then figures the curve of the autocorrelation function with the time τ. When the function value decreases to 1-1/e of the initial value, the obtained time τ is the time of the phase space reconstruction.

The Cao method proposed by Liangyue Gao is mainly used to obtain the embedding dimension of time series, the process of specific computation is shown in references[15-16]. In this method, if the time series is the attractor, when $m > m_o$, will stop changing, that is +1 is the minumum. Actually, when $E_1(m) > 0.99$ for the first time, $E_1(m)$ will stop changing. Because all values are independent for the random time series, for any embedding dimension, $E_1(m)$ is equal to 1 permanently. But for the chaotic sequence, the value of $E_1(m)$ relates to the value of m, which is not a constant value. So undulations of $E_1(m)$ is as the measure of the deterministic component in signals in a sense.

3.2. The largest Lyapunov index

Lyapunov index is the index of divergence in the quantitative initial closed orbit and the chaotic traffic of the estimated syetem,and it can reflect the level of the chaotic traffic from the chaotic dynamic system. $\lambda < 0$ represents the contraction of the phase space orbits and the stability of movement and it is not sensitive to initial conditions. When $\lambda > 0$, the orbits of the phase space is separated rapidly, and it's sensitive to initial conditions for a long time, so the motion is in chaotic state. Geliboji has verified that if Lyapunov index is greater than zero, it can be sure that the chaos is present.

The Small Data Method[11] is a method of the maximum Lyapunov exponent, calculating the chaotic time series $\{x_1, x_2, ..., x_N\}$. Given the chaotic time series , the embedding dimension m, and the time delay τ, then the number of vectors in the reconstructed phase space is $M = N - (m-1)\tau$, the phase points in m-dimensional phase space is

$$\begin{cases} Y_j = \{x_j, x_{j+\tau}, ..., x_{j+(m-1)\tau}\} j = 1, 2, ..., M \\ \mathrm{m} > 2\mathrm{d}+1 \end{cases} \tag{5}$$

the nearest point Y_{jj} of each point Y_j is found in the phase space, and limits the temporary separation, so

$$d_j(0) = \min_{jj} ||Y_j - Y_{jj}|| \quad |j - jj| > P \tag{6}$$

where P is the average period of the time series. Then calculate out the distance $d_j(i)$ after discrete time steps of every point on the phase space Y_j, that is

$$d_j(i) = |Y_{j+i} - Y_{jj+i}|, i = 1, 2, ..., \min(M-j, M-jj) \tag{7}$$

Finally, the average of all $\ln d_j(i)$ of j coorelated with every i is calculated, that is

$$y(i) = \frac{1}{q\Delta t} \sum_{j=1}^{q} \ln d_j(i) \tag{8}$$

where q is the number of $d_j(i)$, Δt is the period of samples. Use the least square method to obtain the regression line, then the slope of the line is the maximum Lyapunov index.

3.3. Correlation Dimension

GP Algorithm[13,14,17] is proposed by Grassberger and Procaccia in 1983, which calculates the correlation dimension of attractor from the time series.

For a pair of phase points and on m-dimensional space, suppose the distance between them is $r_{ij}(m)$, defined as

$$r_{ij}(m) = ||Y_i - Y_j|| = \max_k |x_{i+k} - x_{j+k}| \tag{9}$$

where $k = 0, 1, ..., m-1$. The definition of the correlation integral function is:

$$C_m(r) = \frac{1}{M(M-1)} \sum_{i=1}^{M} \sum_{j=1}^{M} H(r - r_{ij}(m)) \tag{10}$$

where r is the radius of super ball in m-dimensional phase space; M is the number of vectors of the reconstruction phase space; is Heaviside function:

$$H(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{11}$$

When the value r is in a certain range, the correlation integral function is as shown in (12),

$$C_m(r) = Kr^{D(m)} \tag{12}$$

$D(m)$ is called the correlation dimension, the formula is equation (13) below.

$$D(m) = \lim_{r \to 0} \frac{\ln C_m(r)}{\ln(r)} \tag{13}$$

In practice, m is usually increasing from small to large, but D is constant, that is the straight line in $\ln C_m(r)$-$\ln(r)$. Apart from the slope of a straight line with 0 and ∞, inspect the best-fitting straight line during them, and the slope of the straight line is D.

3.4. Kolmogorov Entropy

Kolmogorov entropy is used to measure the degree of confusion or disorder of the system movement13,14,17. Considering a n-dimensional dynamical system, its phase space is divided into each n-dimensional cube box with side length r, for an attractor of the state space and the track $x(t)$ falling on the attract domain, take a very small amount of time interval τ,$P(i_0, i_1, ...i_m)$ describes the joint probability when the starting time of the system orbit is in the i_0-th lattice,$t = \tau$ is in the i_1-th lattice and $t = m\tau$ is in the i_m-th lattice. So the defination of Kolmogorov entropy is:

$$K = -\lim_{\tau \to 0} \lim_{r \to 0} \lim_{m \to \infty} \frac{1}{m\tau} \sum_{i=i_0}^{i_m} P(i) \ln P(i) \tag{14}$$

The defination of Renyi entropy with q orders is:

$$K_q = -\lim_{\tau \to 0} \lim_{r \to 0} \lim_{m \to \infty} \frac{1}{m\tau} \frac{1}{q-1} \log_2 \sum_{i=i_0}^{i_m} P^q(i) \tag{15}$$

where K_0 is the topological entropy,K_1 is the Kolmogorov entropy and K_2 is the Renyi entropy with two orders, and in general,K_2 is a good estimation of K_1.

The relationship of K_2 and ${C_m}^2(r)$ is:

$$K_2 = -\lim_{\tau \to 0} \lim_{r \to 0} \lim_{m \to \infty} \frac{1}{m\tau} \ln {C_m}^2(r) \tag{16}$$

For the discrete time series, the fixed delay time τ and the embedding dimension m, (16) can be simplified as:

$$K_2 = -\lim_{r \to 0} \frac{1}{m\tau} \ln {C_m}^2(r) \tag{17}$$

Because that when $r \to 0$, the relationship of ${C_m}^2(r)$ and r is shown as:

$$K_2 = \lim_{r \to 0} \frac{1}{m\tau} \ln \frac{r^D}{{C_m}^2(r)} \tag{18}$$

In the actual calculation, figure the curve of $r - K_2$ to study the best linear fitting line, then the intercept of that line in the vertical axis is the required stable estimation of Kolmogorov entropy K.

4. EXPERIMENTAL ANALYSIS

The test uses three-supporting two cross-rotor system, the rub-impact between dynamic and static components of the rotor system achieves to simulate through a rub-impact bracket installed in the rotor base. The rub-impact bracket is installed between the bearing 1 and 2, a retractable screw is installed on the screw hole of the top of the bracket, facing the pivot center along the radial axis, and adjusting the screw can produce rub-impact, as shown in Fig.2. Two sensors are installed on the bearing 1 and 2 respectively. Sensor 1 is on the bearing 1, sensor 2 is on the bearing 2, AE is on the pivot center. When two sensors receive the sound source signal of rotor friction, the sampling frequency is 2MHz, and points are 32768. Fig.3 is, when two sensors are respectively at $(x_1, y_1, (0, 0))$ and $(x_2, y_2) = (43, 0)$ and the distance between AE source and sensor 1 is 20cm, the sound source signal of rotor friction received by the sensor.

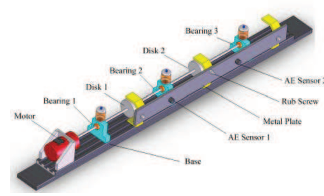


Figure 2: Rotor rub-impact testing equipment

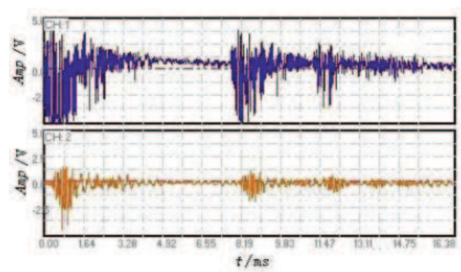
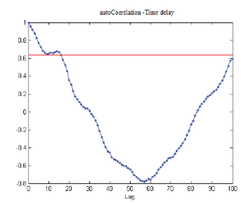
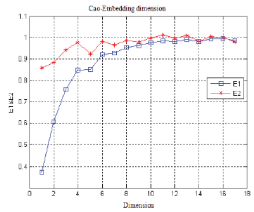


Figure 3: The measured acoustic emitted signals received by sensor

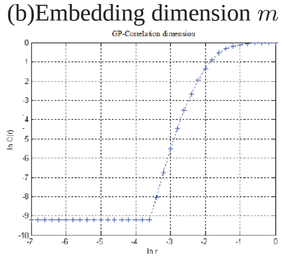
It can be seen from Fig.4 (a) that when the correlation function drops to 1-1/e, the delay value τ takes 17. In Fig.4 (b), the blue line indicates the trend of $E_1(m)$, when m=13,$E_1(m)$0.99 for the first time, so the minimum of embedding dimension is 14. At the same time, $E_2(m)$ changes with the change of m, verifying the chaotic nature of the rub-impact from another point of view. The data from Fig.4 (c) is conducted on linear line fitting, the correlation dimension can be obtained as D=2.5052. The aver-



(a)Time delay τ

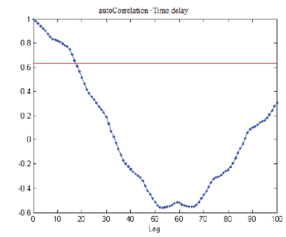


(b)Embedding dimension m

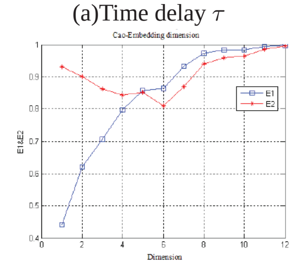


(c)Correlation dimension D

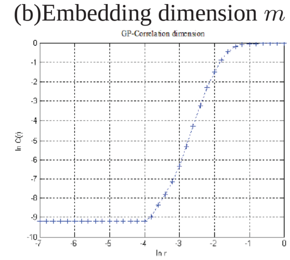
Figure 4: Chaotic characteristics of AE signal of sensor 1



(a)Time delay τ



(b)Embedding dimension m



(c)Correlation dimension D

Figure 5: Chaotic characteristics of AE signal of sensor 2

age period P = 100, so it can find the maximum Lyapunov index is 0.0023, and the Kolmogorov entropy is 0.0077.

It can be seen from Fig.5 (a) that time delay τ=18. In Fig.5 (b), when m=10,$E_1(m)$0.99 for the first time, so the minimum of embedding dimension is 11. The data from Fig.5 (c) is conducted on linear line fitting, the correlation dimension can be obtained as D=2.2513. The average period P = 100, so it can find the maximum Lyapunov index is 0.00046, and the Kolmogorov entropy is 0.0065.

This paper receives the correlation dimension, largest Lyapunov index, the Kolmogorov entropy and another three characteristic variables of acoustic emitted signals received by two sensors as the inputs of algebraic neural network. As the AE source is on the axis of rotation, so the coordinates of the friction sound source are one-dimensional variables and the number of neurons exported by the network is 1.

The test of rotor friction performs 100 times, and 'sym4' is used to pretreat the original signal to eliminate the interference of noise on the original signal. The denoised signals after the normalization will divide the dates into 2 parts, 90 groups of which are as the training samples, where the correlation dimension, largest Lyapunov index and the Kolmogorov entropy are as the input variables to train the neural network, and the remaining 10 groups of which are as the test samples to test the predicted effects of model. Use the network designed in this paper to test the remaining 10 test samples, and the comparison between the predicted results and the actual results is as shown in Table 1.

Table 1: Comparison of Stiffness and Damping Coefficients Under 2 Sets of Rotor Unbalance

Sound source location (from sensor 1)(cm)	Network prediction (cm)	error(%)
3	3.0148	0.49
5	4.9736	0.53
8	8.0659	0.82
10	10.1092	1.09
15	15.1871	1.25
18	18.2033	1.13
22	21.7655	1.07
27	27.3209	1.19
35	34.7164	0.81
40	39.8375	0.41

From Table 1 we can see that, the non-dynamics features expressing the source signal of rub-impact acoustic emission (AE), which extracted from the chaotic time series, are used into the GMM with TDNN, and the precision of sound source location is very high, all errors are collected in 1%. The distance between two sensors is 43cm, when the sound source is at the symmetrical position such as 3cm and 40cm, the error of prediction results are nearly the same. This is also indirectly proved the feasibility of the proposed algorithm in this paper applied into the rubbing position.

5. CONCLUSIONS

When the rotor is rubbing, the vibration has obvious nonlinear characteristic. This article extracts the features that can describe the chaotic nature of system such as correlation dimension, Kolmogorov entropy and Lyapunov index, and make them as the inputs of algebraic neural network applied to the Acoustic Emission source location of friction. Experimental results show that the method can predict the location of acoustic emission sources, and overcome many problems of the TDOA location method, as well as simplify the computation.

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First Author was born in 1968. He recieved his B.E. Degree in Industrial Electric Automation from Harbin Shipbuilding Engineering Institute in 1991, the M.S.degree in 1994, and the Ph.D. degree in 2008, both from Southeast University. Currently, he is an associate professor with the National Engineering Research Center of Turbo generator Vibration of School of Energy and Environment, Southeast University, Nanjing, China.He worked in areas of measurement technology and instruments, fault analyses and signal processing. Recently he has been working on acoustic emission technology for rotating machinery fault diagnosis applications.