Application of GMM-UBM with an embedded AANN in the acoustic emission signal recognition

Cheng Xinmin[1]*, Li Jing[2], Jiang Yunliang[2], Gao Ge[2]

[1]*School of Information Engineering, Huzhou Teachers' College, Huzhou 313000, Zhejiang, PR China*

[2]*School of Information Science and Engineering, Southeast University, Nanjing 210096, Jiangsu, PR China*

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Abstract

In this paper, we propose to recognize the Acoustic Emission (AE) signal, by using a Gaussian Mixture Model-Universal Background Model (GMM-UBW) with an embedded AANN. The AANN based GMM-UBW combines the learning ability of neural network and strong distribution capabilities of GMM. And, it trains the model parameters alternatively in order to approach the maximum likelihood. For illustrating the effectiveness of the proposed recognition method for the AE signal, an experiment is conducted. In the experiment, three cases of AE signal are considered, namely with no rub impact, slight rub impact and serious rub impact. The experimental results reveal that the AANN based GMM-UBW outperforms the GMM, with respect to the recognition rate, for any case of AE signal. For the case of slight rub impact, the GMM-UBW and that with embedded AANN both have the worst recognition performance, among the three cases. And, the proposed method has the biggest improvement for this case.

Keywords: acoustic emission; Auto-Associative Neural Network; Gaussian Mixture-Universal Background Model

1 Introduction

The acoustic signal processing has always been a hot topic in the world [1-4]. The acoustic emission is a typical application. The rub-impact between rotor and stator is a common fault in rotating machines [5]. Effective recognition of the rub-impact plays an important role in safe and stable running of the rotating machines [5]. The AE recognition can realize the fault recognition of the AE source by using the AE signal [6-9]. And, it is a non-destructive detection method [6-9]. By employing the tool of pattern recognition [10], the AE signal can be properly classified. The AE recognition can realize the effective fault recognition and the evaluation of the safety performance of the correspondding material.

Gaussian Mixture Model-Universal Background Model (GMM-UBM) plays an important part in the field of pattern recognition (e.g., speech recognition) [11-16]. It can approach the AE data correctly in AE recognition and decrease the total difference between various signals. The artificial neural network (ANN) can simulate the human brains' structure and faculty using parallel processing technology [10]. It can approximate almost any non-linear mapping. And thus, in the AE recognition, it plays an important role where the model construction cannot be reached and in the comprehensive recognition. ANN is an effective tool in analysing the AE signal [10]. Auto-Associative Neural Network (AANN) possesses a special symmetric structure, and is proven to be a successful algorithm in signal detection [15-16].

In order to improve the performance of the AE signal recognition, the AANN is embedded into the GMM-UBM. Firstly, the feature vectors are input into GMM-UBM after being processed by AANN transfer. The output results are used to modify the AANN model through error back propagation. As two models are trained alternatively, the maximum likelihood can be approximated and a superior recognition rate can be achieved.

2 AE recognition based on GMM-UBM with an embedded AANN

2.1 APPLICATION OF AANN IN THE AE RECOGNITION

AANN, proposed by Kramer in 1990s, is a special forward neural network, where the identity mapping is adopted. The topology structure of the AANN is illustrated in the following Figure 1.

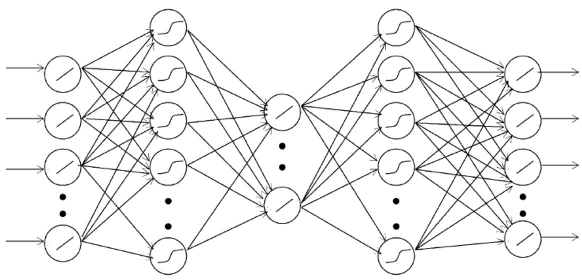

FIGURE 1 Auto-Associative Neural Network

The topology space of the AANN is set through associative learning. Then, the data coding and compression are implemented in the network bottleneck. Afterwards, the characteristic information of the process is obtained and the

*** Corresponding author** e-mail: chengxinmin@hutc.zj.cn

noise is filtered. Finally, the output (approximately) identical to the input is obtained. After the model training, the signal with noise being cancelled can be obtained by inputting the original signal with noise into the model. In the compression process, the characteristic dimension is reduced and the signal in higher-dimension space is projected into lower-dimension space. The linear combination of the principle components is utilized to represent the signal's high-order statistical property. And thus, the AANN can be taken as a non-linear principal component analysis (PCA) model.

In the field of pattern recognition, the data in the feature space generally has a complex distribution. However, as for the GMM, the data in the feature space are represented by statistical quantities of first and second orders and the mixture weights, and number of mixture is generally confined. So, the AANN, which is a non-linear model possessing multi-layer perceptron, is considered to be a practical model suitable for processing complex sound signal. It can obtain the error curve of the feature space, which matches the distribution of the training data. The approximation ability of the network to data can be observed, by training the error curve.

In the following, we will deduce the rule for training the model parameters of the AANN model. The basic idea of the training rule of the neural network is gradient descent method. Let $\vec{w}$, D and d be the weights, the training set and an instance in the set, respectively. The error E is defined as follows:

$$E(\vec{w}) = \frac{1}{2}\sum_{d\in D}(t_d - o_d)^2 , \tag{1}$$

where t_d and o_d are the expected and true outputs. Starting from some set of initial coefficients, the gradient descent method can be utilized to modify the coefficients of the model.

$$\Delta w_i = -\eta\frac{\partial E}{\partial w_i} = \eta\sum_{d\in D}(t_d - o_d)x_{id} . \tag{2}$$

For each layer of a neural network, the weights of the input vector $net_j = \sum w_{ji}x_{ji}$ is transformed through the sigmoid function. The training process from i th hidden layer to the j th output layer is illustrated as follows:

$$\begin{aligned}\frac{\partial E_d}{\partial w_{ji}} &= \frac{\partial E_d}{\partial net_j}\cdot\frac{\partial net_j}{\partial w_{ji}} = \frac{\partial E_d}{\partial net_j}\cdot x_{ji} \\ &= \frac{\partial E_d}{\partial o_j}\cdot\frac{\partial o_j}{\partial net_j}\cdot x_{ji} = -(t_j - o_j)\cdot o_j(1-o_j)\cdot x_{ji}\end{aligned} . \tag{3}$$

Thus, the weight update quantity is:

$$\Delta w_{ji} = -\eta\frac{\partial E_d}{\partial w_{ji}} = \eta(t_j - o_j)\cdot o_j(1-o_j)\cdot x_{ji} = \eta\delta_j x_{ji} , \tag{4}$$

where $\delta_j = -\frac{\partial E_d}{\partial net_j} = (t_j - o_j)\cdot o_j(1-o_j)$ is the error term.

Similarly, for the k th output layer, the training process from the i th input layer to the j th hidden layer is illustrated as follows:

$$\begin{aligned}\frac{\partial E_d}{\partial net_j} &= \sum\frac{\partial E_d}{\partial net_k}\cdot\frac{\partial net_k}{\partial net_j} \\ &= \sum(-\delta_k)\frac{\partial net_k}{\partial o_j}\cdot\frac{\partial o_j}{\partial net_j} \\ &= \sum(-\delta_k)w_{kj}\cdot o_j(1-o_j) = \eta\delta_j x_{ji}\end{aligned} . \tag{5}$$

Thus, the weight update quantity is

$$\Delta w_{ji} = -\eta\frac{\partial E_d}{\partial w_{ji}} = \sum\eta\delta_k w_{kj}\cdot o_j(1-o_j)x_{ji} = \eta\delta_j x_{ji} , \tag{6}$$

where $\delta_j = -\frac{\partial E_d}{\partial net_j} = \sum\delta_k w_{kj}\cdot o_j(1-o_j)$ is the error term.

Summing up the above deduction, the weight update process of the AANN is provided as follows:

Step 1. Set the numbers of layers and nodes for each layer, and the initial weight coefficients.

Step 2. For the output o_k of the training instance $(k \quad t_k)$, calculate the error term from hidden layer to output layer $\delta_k = -(t_k - o_k)\cdot o_k(1-o_k)$.

Step 3. Calculate the weight update quantity $\Delta w_{kj} = \eta\delta_k x_{kj}$ from hidden layer to output layer and update the weight value w_{kj}.

Step 4. Calculate the error term from input layer to hidden layer $\delta_j = \sum\delta_k w_{kj}\cdot o_j(1-o_j)$ according to δ_k.

Step 5. Calculate the weight update quantity from input layer to hidden layer $\Delta w_{ji} = \eta\delta_j x_{ji}$ and update w_{ji}.

Step 6. If the convergence conditions are satisfied, then terminate the iteration. Otherwise, go to step 2.

2.2 IMPLEMENT GMM-UBM IN THE AE RECOGNITION

GMM is a linear combination of multiple Gaussian probability density functions. Any continuous distribution can be approximated with desired precision by using GMM, as long as the number of components in the model is large enough. So, GMM has a wide range of applications, such as speech recognition, image denoising, detection of chemical machining process and mechanical fault diagnosis. For a D dimensional feature vector x_t, the M th order probability density function of GMM is given as follows:

$$p(x/\lambda) = \sum_{i=1}^{M} w_i\cdot p_i(x) . \tag{7}$$

Gaussian Mixed density can be expressed by the mean value, covariance matrix, and mixed weight parameterrization of the total members' density as follows: $\lambda_i = \left\{ p_i,\ u_i,\ \sum_i \right\},\ i = 1,\ 2,\ 3,\ ...,\ M$.

The covariance matrix can be reduced to a diagonal matrix if the individual components are assumed to be independent. Then the D dimensional Gaussian probability density function can be represented as follows:

$$p_i(x) = \frac{1}{(2\pi)^{D/2}\left|\Sigma_i\right|^{1/2}} \exp\left\{ -\frac{1}{2}(x-u_i)' \Sigma_i^{-1} (x-u_i) \right\}. \qquad (8)$$

After obtaining the training vector, the iterative expectation maximization (EM) algorithm can be employed to estimate the maximum likelihood model.

$$p(i \mid x_t, \lambda) = \frac{p_i b_i(x_t)}{\sum_{k=1}^{M} p_k b_k(x_t)}. \qquad (9)$$

Iteratively calculate the weight coefficients, mean value and variance according to the following equations.

$$\overline{p_i} = \frac{1}{N}\sum_{t=1}^{N} p(i \mid x_t, \lambda), \qquad (10)$$

$$\overline{u_i} = \frac{\sum_{t=1}^{N} p(i \mid x_t, \lambda) x_t}{\sum_{t=1}^{N} p(i \mid x_t, \lambda)}, \qquad (11)$$

$$\overline{\sigma_i^2} = \frac{\sum_{t=1}^{N} p(i \mid x_t, \lambda) x_t^2}{\sum_{t=1}^{N} p(i \mid x_t, \lambda)}. \qquad (12)$$

In the pattern recognition of GMM-UBW, verification vectors are input into the AE model and background model, in the test, and the ratio of the two models is calculated. If the ratio is higher than the prescribed threshold, the category of this AE source model is accepted. Otherwise, it is rejected. In other words, the background model provides the model for all the training instances, and sums up the model trend of all the input instances. It works as the denominator in the recognition, and has a normalizing effect on the total test voice scores [3]. Compared with GMM, GMM-UBM reduces the effect of rating difference between different voice signals, to a great extent. And thus, it has superior recognition performance. Moreover, because the AE training data is not enough, the number of GMM's mixture components cannot be set big enough. However, this number should be large enough in order to improve the recognition. The GMM-UBW trained through enough speech data can reduce the limitedness of the model's mixture component number.

GMM-UBW was originally applied to the text-independent speaker identification system. And, it also has applications, combined with support vector machine (SVM) theory, in emotional speech recognition and language recognition.

2.3 GMM-UBM STRUCTURE EMBEDDED WITH AANN

According to the error curve of AANN, a probability distribution matching the given data can be obtained. The distribution relates to the network cell and a kind of gain coefficient. The data distribution is not considered for this AANN. The error curve can only be utilized to verify the training ability of the network model. It, however, cannot provide information for signal construction in mathematical model. The GMM cannot transform the data, change its distribution. Further, the model itself has some limitedness and the matching precision cannot reach the desired requirement, due to the assumption of independence.

In view of the GMM-UBW's strong ability of data distribution and the AANN's excellent learning ability, these two kinds of pattern recognition methods are combined together. And, we proposed to recognize the AE signal by using a GMM-UBW with a AANN being embedded.

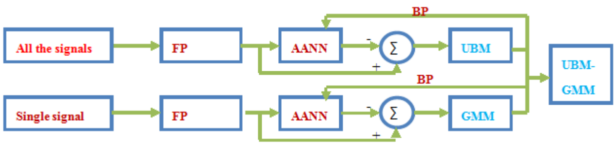

FIGURE 2 GMM-UBM embedded with AANN topping structure

As is illustrated in Figure 2, the training structure is composed of UBM and GMM. And the final output is GMM-UBW model. After extracting the characteristic parameters of the training sound signal, the feature vector is transformed through AANN. The difference between the output of the transformation and the original feature vector is input into the hybrid model. The modified output of the hybrid-model feedbacks the AANN and re-modify the AANN. The above process is repeated until the convergence conditions are satisfied. As for the UBW, the characteristic parameters of all the sound signal are input while the characteristic parameters of GMM are input one by one.

The specific training process is given as follows:

Step 1. Set the values of initial parameters and the convergence conditions of AANN and GMM.

Step 2. Input the characteristic parameters and obtain the error vector.

Step 3. Update the model parameters p_i, u_i and σ_i^2 of GMM while fixing the model parameters of AANN.

Step 4. Input the error vector into the modified GMM and obtain the likelihood probability. Transmit the error to the AANN before backwards and update its model parameter w_i.

Step 5. If the convergence conditions are satisfied, then terminate the iteration. Otherwise, turn to step 2 and continue the above process.

In the above process, the training processes for UBM and GMM are almost the same. The only difference exists in that the parameters of GMM, which is trained after UBM, are optimized based on UBM. This can save a certain amount of training time.

Construct AANN-GMM for each category (the existence of rub-impact or not). After the model training is complete, the recognition of the tested AE signal can begin. Then, input the feature vector into the AANN-GMM and obtain the likelihood probability of the categories. Finally, the recognition results are obtained.

3 Experiments and Discussions

The experimental data in this paper comes from the rotor system equipped with a rub impact bracket. The experimenttal equipment is illustrated in Figure 3. The rotor rub impact signal is produced by adjusting the nut bolt. The sampling frequency is 1MHz. The feature parameter method is adopted in the experiment. The feature of the AE signal is represented by seven simplified wave feature parameters. These seven parameters include the average vibration amplitude of rub impact signal, the maximum amplitude, the dynamic range of vibration amplitude and the reconstructed signal's energy of the first four contact points of the decomposed signal through wavelet package. The AE signals of no rub impact, slight rub impact and serious rub impact are provided in Figures 4, 5 and 6, respectively.

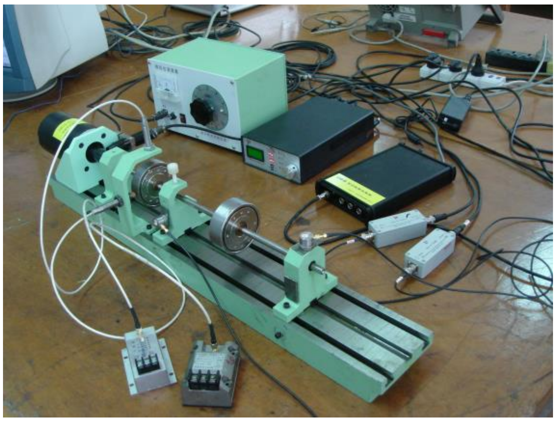

FIGURE 3 Rotor system

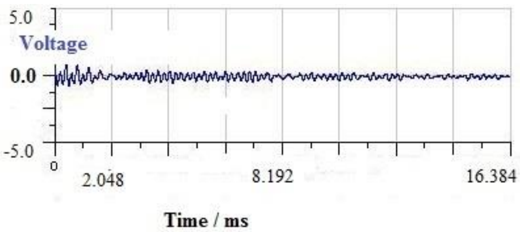

FIGURE 4 AE signal with no rub impact

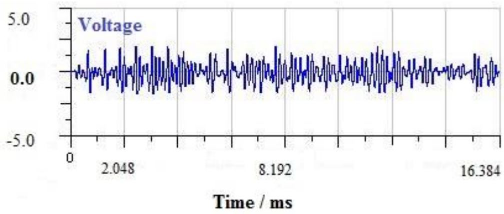

FIGURE 5 AE signal with slight rub impact

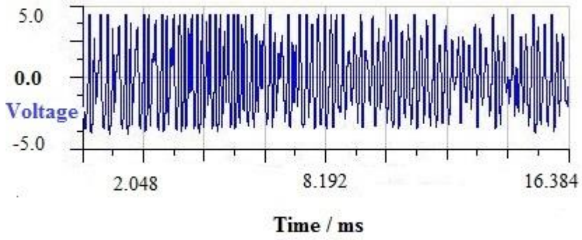

FIGURE 6 AE signal with serious rub impact

The performance of the GMM-UBW and that of the GMM-UBW embedded with AANN are analysed by using the same training data and the same test data. By adjusting the nut bolt, the three cases of AE signal, namely no rub-impact, slight rub-impact and serious rub-impact (all with respect to the rotating axis), are produced. The recognition performance of the above two models are evaluated for the above three cases of AE signal. The recognition rate comparison of the two models is provided in the following Figure 7. And, the recognition improvement of GMM-UBW with embedded AANN, with respect to GMM-UBW, is provided in Figure 8.

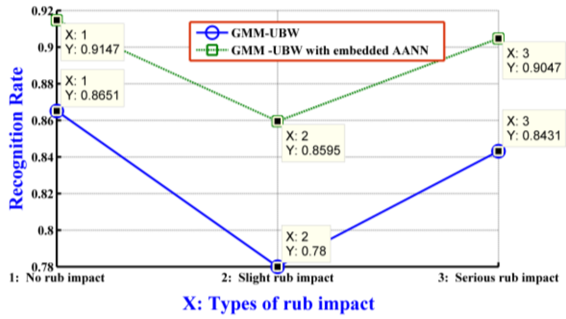

FIGURE 7 Recognition comparison between UBM-GMM and UBM-GMM embedded with AANN

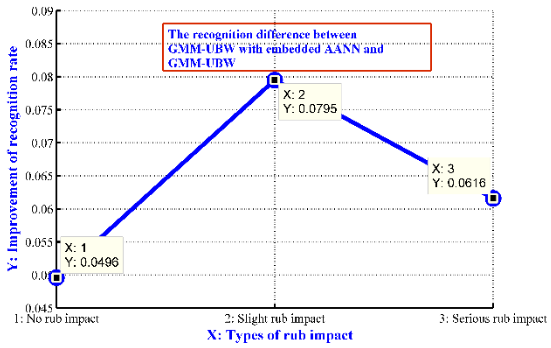

FIGURE 8 Recognition improvement of UBM-GMM embedded with AANN, with respect to UBM-GMM

The experimental results reveal that the GMM-UBW embedded with AANN outperforms the GMM-UBW for the three cases of AE signal separately. Specifically, the recognition rates are improved by 5.75%, 10.10% and 7.76% for the three cases (i.e., no rub impact, slight rub impact and serious rub impact), respectively. The results also reveal that for the case of slight rub impact, the GMM-UBW and that with embedded AANN both have the worst recognition performance, among the three cases. And, the proposed method has the biggest improvement for this case. This indicates that the two models are not sensitive to the sound caused by the AE source. So, further work is required to extract more suitable feature vector, to improve the model structure and optimization algorithm and to better the fault detection efficiency of the AE method.

4 Conclusions

The GMM-UBW with an embedded AANN is proposed to recognize the AE signal and its recognition performance is studied in this paper. The proposed recognition method exploits the superior learning ability of the AANN to train the parameters of the whole model, by means of a two-stage training method. In the training process, the parameters of the GMM-UBM and the AANN are iteratively improved in order to obtain a superior likelihood probability. The experimental results reveal that the recognition rate of the rub-impact can be improved by using the proposed method.

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Authors

Cheng Xinmin

Current position, grades: Master, the Associate Professor of Huzhou Teachers' College
Scientific interest: Intelligent signal processing, Information fusion
Experience: an expert in the field of information fusion

Li Jing

Current position, grades: Master, pursuing the Ph.D. degree in AE signal processing at southeast University
University studies: She received the B.A. degree in electronic information from Hebei University of Engineering, Handan, China, in 2001 and 2005, and the M.Sc. degrees in communication from China University of Mining & Technology, Xuzhou, China, in 2005 and 2008.
Scientific interest: AE signal processing

Jiang Yunliang

Current position, grades: Doctor, the Professor of Huzhou Teachers' College
Scientific interest: GIS, Information fusion
Experience: an expert in the field of GIS and information fusion

Gao Ge

Current position, grades: Master, the Associate Professor of Yancheng Institute of Technology
University studies: She received the B.A. degree information engineering from Southeast University, Nanjing, China, in 2012.
Scientific interest: AE signal processing