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# Fault diagnosis for the motor drive system of urban transit based on improved Hidden Markov Model



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### ABSTRACT

Fault diagnosis for the motor drive system of urban rail transit could reduce the hidden danger and avoid the disaster events as far as possible. In this paper, an improved Hidden Markov Model (HMM) algorithm is proposed for fault diagnosis of motors equipment for urban rail transit. In this approach, the initial value for observation matrix B in HMM is selected based on the predictive neural network and intuitionistic fuzzy sets. Firstly, by predictive neural network the observation probability matrix B is described qualitatively based on its mathematical explanation. Then, the quartering approach is introduced to define the rules between non-membership degree and observation probability matrix B, which obtains the matrix B quantitatively. Next, the selection algorithm for matrix B is given. Finally, the experiments about the motor drive system fault diagnosis of the urban rail transit are made to prove the feasibility for the proposed algorithm.

#### 1. Introduction

Urban rail transit has been the first choice to solve the traffic congestion due to its fast speed, high safe, good punctual, large capacity, etc. As a power equipment of the urban rail transit, the normal operation of the motor drive system is of great significance for the safety operation of the urban rail transit. In its running process, the most common faults are the bearing related faults, rotor windings inter-turn short circuit faults, motor broken bar faults and the other faults, etc. [1]. If these faults are not detected and some effective protective measures are also not taken in time, the fault-nodes will deteriorate even further, which will result in huge loss of personnel and property or even lead to disastrous consequences [2,3]. Therefore, it is of great theoretical and practical significance to reconstruct the motor fault so that the fault-tolerant control (FTC) can be carried out subsequently.

As we know for experience, the vibration signature analysis is one of the most widely used methods for the condition monitoring of the rotating machinery equipment in the actual running. In fact, machine vibration arises due to action-reaction forces acting on the surface-tosurface contacts of moving machine parts [4,5]. In fact, a health machine should keep low level of vibrations. Once there will be security risk in machine equipment, the running signal include various types of vibration signatures.

Based on above discussion, some works about fault diagnosis for motor are proposed, such as, expert system, artificial neural network, fuzzy diagnosis, support vector machine, baye etc. [6]. As one of the intelligent diagnosis a method, HMMs method has been widely utilized because of its unique characteristics, i.e., it not only has a rich mathematical structure and a solid theoretical foundation, but also has some advantages. For example, the real model can be explained reasonably, the training sample is small and the classification precision is high, etc. It is the aforesaid reason that makes the HMMs widely used in the field of fault diagnosis.

Recently, there are many reports about the fault detection and diagnosis for various motors based on HMMs [7-13]. The authors in [7,8] presents a novel method based on HMM technique and pattern recognition feature to diagnosis and detect motor bearing fault. In order to reduce the computation burden, an optimal method is proposed to select the order of HMM based on information entropy in [9]. For the short circuit fault of a motor, a novel diagnosis method for insulation failure of motor windings was constructed by combing with impulse testing and pattern recognition based HMM in [10]. Meanwhile, a HMM-based fault diagnosis algorithm was proposed to monitor the safety of speed-up and speed-down of rotating machinery in [11]. In reference [12], a method for faults diagnosis of rotating machinery is put forward based on 2-dimension HMM. In order to classify the state condition of running, a condition classification algorithm in [13] was conducted based on HMMs processing information obtained from vibration signals. In this paper, the authors had designed an on-line fault classification system with the adaptive model and re-estimation algorithm. The system may achieve a good rate of recognition in motor drive systems.

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Nomenclature		S <sub>i</sub>	fault mode of MDS
		0	judgment matrix of membership
HMMS	Hidden Markov Models	Α	intuitionistic fuzzy set
N	number of states in HMMs	$\mu_A$	membership function of A
Т	length of the observation sequence	ŶΑ	non-membership function of A
В	observation probability matrix	$\pi_A$	hesitancy degree of $x$ belongs to $A$
$\pi_i$	initial state distribution of <i>i</i> state	$\sigma_{A}$	non-hesitation degree index
b <sub>ii</sub>	element of B	$Norm(\cdot)$	$L^2$ normalization
a <sub>ij</sub>	state transition probability	É	normalization relation of E
$p_i$	input of hidden layer	ξ	first demarcation point in [0,1]
$\mu_{ik}$	mean vector of N	η	second demarcation point in [0,1]
$U_{ik}$	covariance matrix of N	θ	third demarcation points in [0,1]
$\omega_{ij}$	weights between <i>j</i> and <i>i</i>	$e(\xi,\eta,\theta)$	mapping relation corresponding to every variable $(\xi, \eta, \theta)$
$\omega_{ki}$	weights between <i>i</i> and <i>k</i>	p.(•)	probability density of random variance
$x_i$	input vectors of network	$\xi_t(i,j)$	probability in the state of $S_i$ at $t$ and state of $S_i$ at $t + 1$
$f_i$	activation function of network	$\gamma_t(\cdot)$	mean probability of running state at t
$\theta_k$	bias of each node k	$\alpha_t(\cdot)$	local probability in running state at t
m <sub>i</sub>	output of each hidden node <i>i</i>	$\beta_t(\cdot)$	probability of observation sequence at t
output <sub>k</sub>	output of each output node k	$\varphi_{\cdot}(\cdot)$	distribution function of probability
E	error sum of squares for output	$P(\cdot   \cdot)$	conditional probability
$e_{ij}$	element of <i>E</i>		

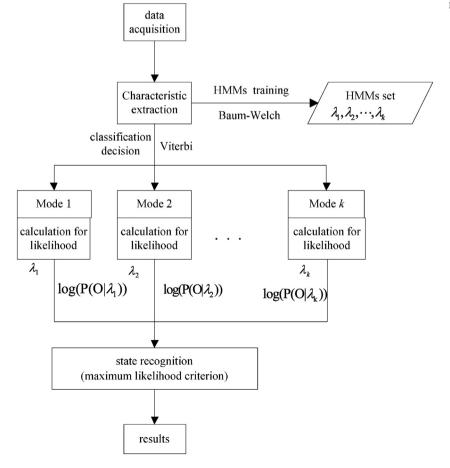
The main idea of these works are that the feature vectors, which are obtained by the FFT, wavelet transform, bispectrum, etc., are used as fault features, respectively. In addition, the obtained fault features are used as the observation time sequences which are fed to the HMMs. In actual application, by the Baum-Welch [14,15], every HMM model is trained in accordance with the training samples selected randomly from the fault characteristic, obtaining the HMMs. Subsequently, the test samples are regarded as the inputs of the obtained models to achieve

the likelihood for various models via the Viterbi algorithm [16,17]. Finally, the fault diagnosis results are obtained based on the criterion of maximum likelihood. The flow frame is shown as Fig. 1.

Fig. 1 indicates that the model training is one of the most important problems in fault diagnosis. However, the Baum-Welch algorithm may realize properly the model training, it still exists some defects. So it is necessary to solve these difficulties by some improved algorithms.

To solve the problem, some studies have demonstrated that the

Fig. 1. Flow diagram of fault diagnosis based on HMM.



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