Journal of Applied Sciences

ISSN 1812-5654

science alert

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Journal of Applied Sciences 13 (23): 5632-5637, 2013
ISSN 1812-5654 / DOI: 10.3923/jas.2013.5632.5637

Faults Diagnosis for Automotive Engine Based on CHMM

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Abstract: Faults behaviors of automotive engine in running-up stage are shown a multidimensional pattern that evolves as a function of time (called dynamic patterns). It is necessary to identify the type of fault during early running stages of automotive engine for the selection of appropriate operator actions to prevent a more severe situation. In this situation, the Faults diagnosis method based on continuous HMM is proposed. Feature vectors of main FFT spectrum component are extracted from vibration signals and looked up as observation vectors of HMM. Several HMMs which substitute the types of faults in automotive engine vibration system are modeled. Decision-making for faults classification is performed. The results of experiment are shown the proposed method is executable and effective.

Key words: Pattern recognition, faults diagnosis, CHMM, automotive engine

INTRODUCTION

Many techniques in pattern recognition deal with static environments: the class distributions are considered relatively constant as a function of the time in which feature vectors are acquired. However, In some systems, time often plays a secondary role: It should be incorporated in the feature extraction procedure. For practical recognition tasks, the assumption of stationarity of the class distributions may not be hold. Alternatively, information in sequences of feature vectors may be used for recognition. We will call both groups of problems dynamic pattern recognition problems. A dynamic pattern is a multidimensional pattern that evolves as a function of time (Ypma, 2001).

A set of feature vectors can be looked upon as the result of independent draws from a multi-dimensional distribution. All temporal information should now be present in each feature vector. Identification problem may then be based on the dissimilarity of a set of newly measured feature vectors with respect to a set of known templates.

HMMs have been proved to be one of the most widely used tools for learning probabilistic models of dynamical time series. HMM can model dynamical behaviors variation existing in the system through a latent variable (hidden states). HMM method that is used for faults diagnosis is often seen in reference literature (Ypma, 2001; Shao *et al*., 2013; Ocak and Loparo, 2005; Feng *et al*., 2006).

For automotive engine, it is necessary to identify the type of faults during it's early stage for the selection of appropriate operation actions to prevent a more severe situation, or to mitigate the consequences of the fault. It is not easy for an operator to identify the type of faults accurately, using the information given by instruments and alarms, with a limited time interval. Therefore, the use of a computer-based Fault diagnosis is recommended. This method is intended to support an operator's decision-making, or to provide input signals fro a computerized faults monitoring system and a computerized operating-procedure management system.

This study is only focused on the faults diagnosis of automotive engine in the running-up stage based on continuous HMM.

PROBABILITY THEORY OF FAULTS DIAGNOSIS

Faults diagnosis problem of automotive engine is defined the classification of type of faults, ω_j, given sequential input pattern X_t at time t. Input pattern X_t is mathematically defined as an object described by a sequence of features at time t(Shao *et al*., 2013):

$$X_t = (x_1, x_2, \ldots, x_d) \tag{1}$$

The space of input pattern X_t consists of the set of all possible pattern: $X_t \subset R^d$, R^d is a d-dimensional real vector space.

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The k observed data up to time t is defined as:

$$\Phi_{t-k} = \{X_{t-k+1}\ldots, X_{t-1}, X_t\} \tag{2}$$

The set of possible fault types ω_j forms the space of classes Ω:

$$\Omega(t) = \{\omega_1, \omega_2, \ldots \omega_c\} \tag{3}$$

where, c is the number of classes.

The faults diagnosis task can be considered to be the finding of function f which maps the space of input patterns Φ_{t-k} to the space of classes Φ.

The vibration signals of automotive engine in running-up stage often exhibit sequentially changing behaviors. If one short-time period is defined to a frame, the probability of a particular frame transition is different for each type of faults. Therefore, the probability of frame's existence and of a particular transition between frames, can be statistically modeled. The probability of specific signal is already known and is called prior probability. When identifying a specific fault, a decision can be made only by selecting the type of signal ω with the highest a prior probability P(ω). The decision is probably unreasonable. It is more reasonable to determine the type of time series after observing the trend of vibration signals of major variables, namely, to get the conditional probability $P(\omega|\Phi_{t-k})$. This conditional probability is called a posterior probability. Decision-making based on the posterior probability is more reliable, because it employs a prior knowledge together with the observed fault features. Classification of an unknown pattern Xt corresponds to finding the optimal model $\hat{\omega}$ that maximizes the conditional probability $P(\omega|\Phi_{t-k})$ over the whole time series of the type ω. One can apply Bayes rule to calculate the a posterior probability:

$$P(\hat{\omega}|F_{t-k}) = \max_{\omega} \frac{P(F_{t-k}|\omega)P(\omega)}{P(F_{t-k})} \tag{4}$$

The conditional probability $P(\omega|\Phi_{t-k})$ comes from comparing the shapes of fault models with the input observations while the prior probability P(ω) comes from the fault probability. Since $P(\Phi_{t-k})$ is independent of $\hat{\omega}$:

$$P(\hat{\omega}/F_{t-k}) \propto \max_{\omega}\{P(F_{t-k}|\omega)P(\omega)\} \tag{5}$$

In fact it is difficult to calculate an a priori probability P(ω) which satisfy the following equation:

$$\sum_{j=1}^{c} \omega_j = 1 \tag{6}$$

The HMM can successfully treat an identification of faults of dynamic pattern under a probabilistic or statistically framework.

In this faults diagnosis problem, the HMM is used to estimate the conditional probability $P(\omega|\Phi_{t-k})$.

DESIGN OF FAULTS DIAGNOSIS BASED ON HMM

Vibration feature vector extract: The vibration signals are sampled with various frequencies according to the velocity of automotive engine running in the method of complete alternation. Each running alternation we can gain 64 points sample of vibration signal. We repeat this process with 8 complete alternations. Thus 512 points sample is available and saved to disk. For the 512 points sample, we can get FFT spectrum with the frequency that is the multiple or half of running frequency of automotive engine. Figure 1 shows the vibration wave and FFT spectrum of samples.

In the Fig. 1 the note "x" is the running frequency of the automotive engine. From the FFT spectrum we can get the Xt as following:

$$X_t = \{\frac{1}{2}x, x, 2x, 3x, 4x, 5x\}$$

Training of HMM: According to the above definition of an HMM, there are three problems of interest (Carmona *et al*., 2013; Feng *et al*., 2002; Shao *et al*., 2013).

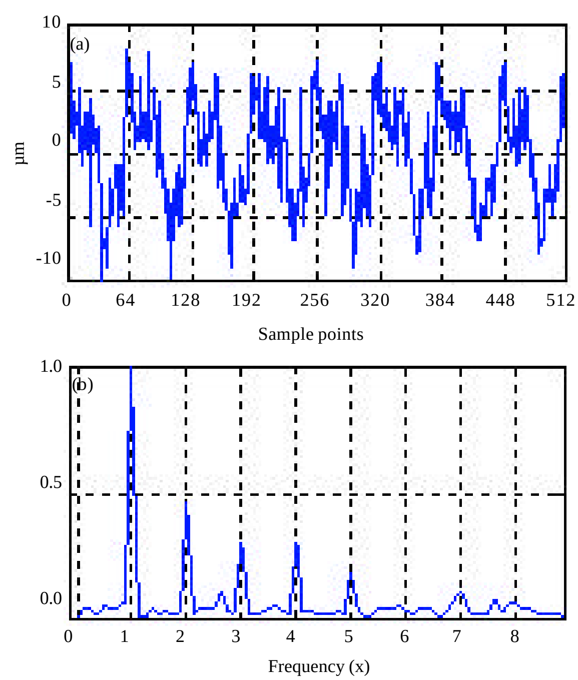

Fig. 1: (a) Vibration wave and (b) FFT spectrum of vibration

- **Evaluation problem:** Given an HMM λ and a sequence of observations, $O = o_1, o_2, o_3 \ldots o_{T-1}, o_T$, what is the probability that the observations are generated by the model, $P(O|\lambda)$
- **Decoding problem:** Given a model λ and a sequence of observations, $O = o_1, o_2, o_3 \ldots o_{T-1}, o_T$ what is the most likely state sequence in the model that produced the observations
- **Learning problem (training problem):** Given a model λ and a sequence of observations, $O = o_1, o_2, o_3 \ldots o_{T-1}, o_T$, how should we adjust the model parameters A, c_{jm}, μ_{jm}, Σ_{jm} and π in order to maximize $P(O|\lambda)$

The Evaluation Problem can be solved by Forward Algorithm and Backward Algorithm. The problem also can be solved by Viterbi Algorithm. The Decoding Problem can be solved by Viterbi Algorithm. The Training Problem can be solved by Baum-Welch Algorithm (Feng *et al*., 2002; Shao *et al*., 2013).

The Training Problem is discussed in this study. The all steps for training of an HMM is as following:

Input the numbers of hidden states, initial probability distribution π, initial state transition probabilities, the error e of iteration, the maximization number of iteration L and observations O.

Initial Gauss function parameters, $\bar{c}_{jm}$, μ_{mj} and Σ_{mj} are estimated by k-means algorithm. Then the initial HMM λ_0 is gained.

According to the Baum-Welch Algorithm, the each parameters A, c_{jm}, μ_{jm} and Σ_{jm} of HMM are re-estimated. In this step, Multi-observation (from various load conditions) can be considered. Therefore, the HMM $\bar{\lambda}_i$ re-estimated by the i-th iteration.

According to the Viterbi Algorithm, the output probability $(PO|\bar{\lambda}_i)$ of re-estimated HMM $\bar{\lambda}_i$ with the observations O is calculated. Then increasing error of output probability between the twice iterations. If the error is satisfied the given error e in the first step, the re-estimated HMM is taken as the final HMM. But if the error is not satisfied given the condition error e, then calculation flows to the step 3.

If the number of iterations exceeds maximization number L, then the training exits.

The training flowchart is shown in Fig. 2.

It is important for initial HMM. The description on the initial HMM is detail in Reference (Feng *et al*., 2002; Zheng and Xie, 2013).

Faults diagnosis by HMM: After detecting the presence of a fault in automotive engine, the next goal is diagnosis of fault identification (Fig. 3). Diagnosis of a fault, therefore, identifies the source of the fault. For such purpose, a HMM for the normal condition is necessary but is not sufficient. We also need to train HMMs to represent the automotive engine faults that are of interest. Once the models are trained, a automotive engine fault can be diagnosed by following the steps shown in Fig. 4.

The c types of faults are considered, the probabilities of the observation sequences given all the HMMs in the previously modeled by history database. The HMM which the probability is maximum, determines the types of fault.

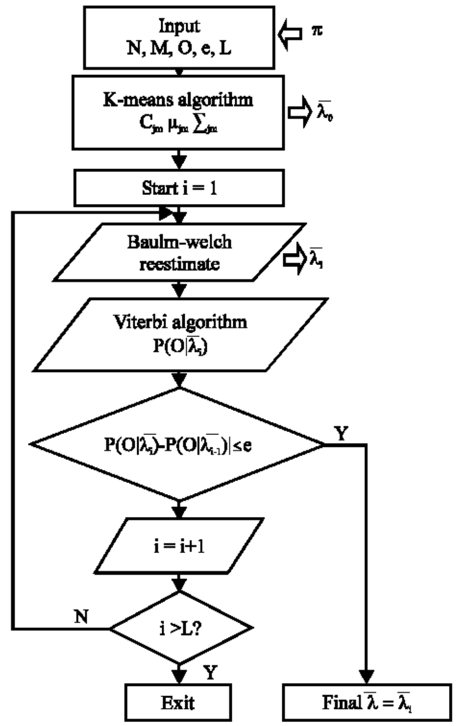

Fig. 2: Flowchart for training of HMM

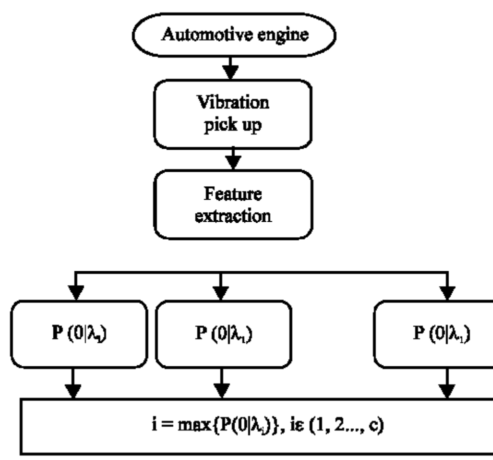

Fig. 3: Faults diagnosis by HMM

Fig. 4: Positions of measuring sensor

EXPERIMENTS AND RESULTS

Experiments setup: The engine vibration belongs to rotating machinery vibration. The implementation of rotating machinery vibration monitoring and fault diagnosis technology includes four steps: Vibration signal acquisition, extraction of feature information, state identification and diagnosis decision- making. Vibration signal acquisition is the premise of fault diagnosis and the extraction of information feature is the key to fault diagnosis; in the process of vibration monitoring and fault diagnosis of civil aviation engine, the feature extraction of vibration fault has played an increasingly important role, so the effective and accurate feature extraction will directly determine the implementation of the latter two steps. To accurately and effectively utilize sensors to acquire vibration information of the rotating machinery is the basic requirement to the abnormal findings as well as quick and accurate fault diagnosis. At the same time, how to extract the feature information which can reflect the healthy state of the rotating machinery using the vibration signal measured by sensors is the key factor to ensure the accuracy of fault diagnosis.

Three types Faults simulation experiments are implemented on automotive engines. Vibration signals are extracted evenly from engine. Then feature vectors are extracted from these vibration signals by FFT spectrum method (described in section 3.1). Finally a sequence of feature FFT vectors are formed into the observation O. Where,

$$O = \{X_1, X_2, \ldots, X_{150}\}$$

During the experiment, vibration data was collected using three 5 mm piezoelectric sensors. A high-speed computer-based analog-to-digital converter was used to convert and store the acquired vibration data including the optical triggering signal into the computer memory.

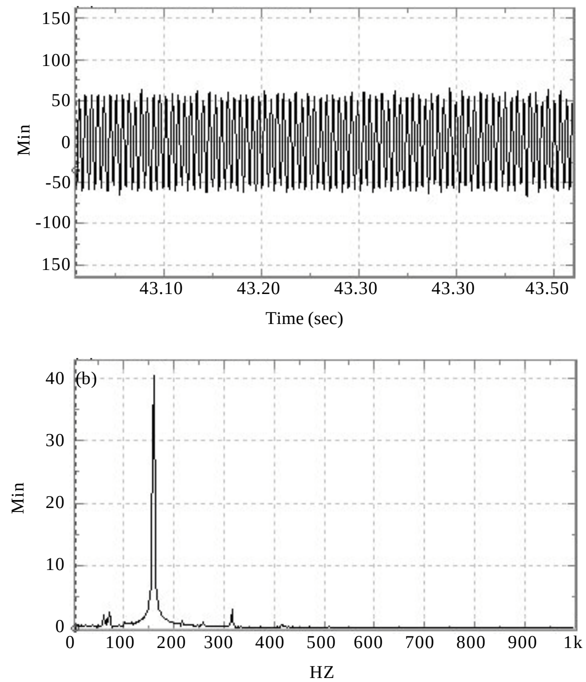

Fig. 5: Time series and power spectrum of normal vibration stage

The positions of sensor mounted are shown in Fig. 5. The vibration data of this study is collected from the sensor. The accelerometer was mounted on the automotive. On the other words, the faults diagnosis is implemented based three sensors.

Data was collected for four different fault conditions: (1) Normal (N), (2) bolt loose fault (L), (3) output axis whirling fault (W) and (4) input air channel fault (I). Vibration signal changes because of above faults. The signal of faults were introduced into computer to analyse its character.

Faults diagnosis result: The HMMs which represent four conditions of (1) normal (N), (2) bolt loose fault (L), (3) output axis whirling fault (W) and (4) input air channel fault (I)are modeled from the initial Model in Fig. 6. The number of the model density used M=5 mixtures.

As seen from the above figures, the probabilities of a given data set is largest correspond to the given HMM which represents the condition of the data.

The results verified that the proposed method in this study is able to detect and identify the faults of automotive engine in running-up stage. (1) normal (N), (2) bolt loose fault (L), (3) output axis whirling fault (W) and (4) input air channel fault (I).The recognition result is shown in Table 1.

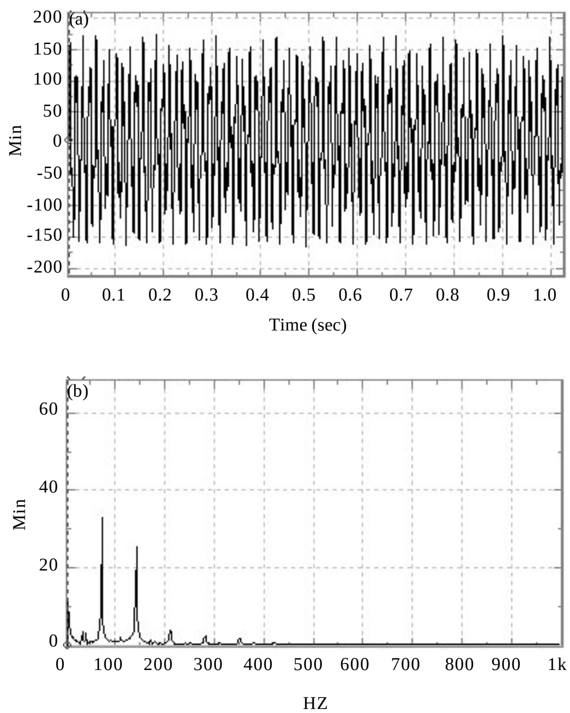

Fig. 6: Time series and power spectrum of bolt loose fault

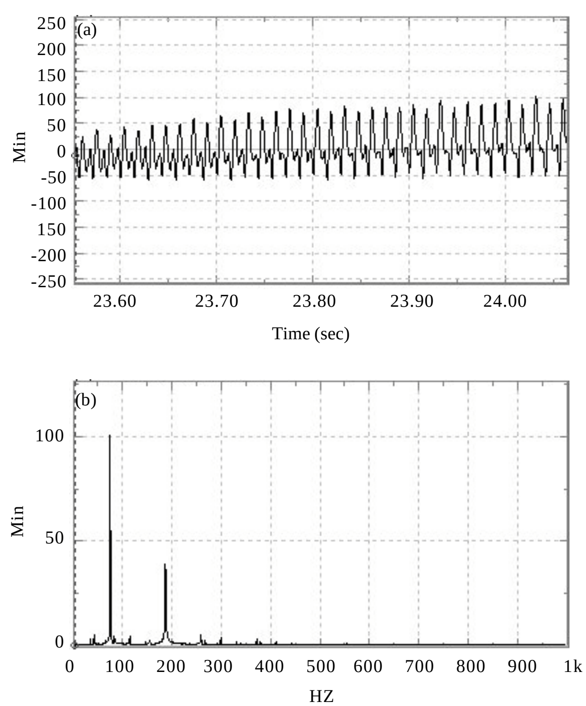

Fig. 7: Time series and power spectrum of output axis whirling fault

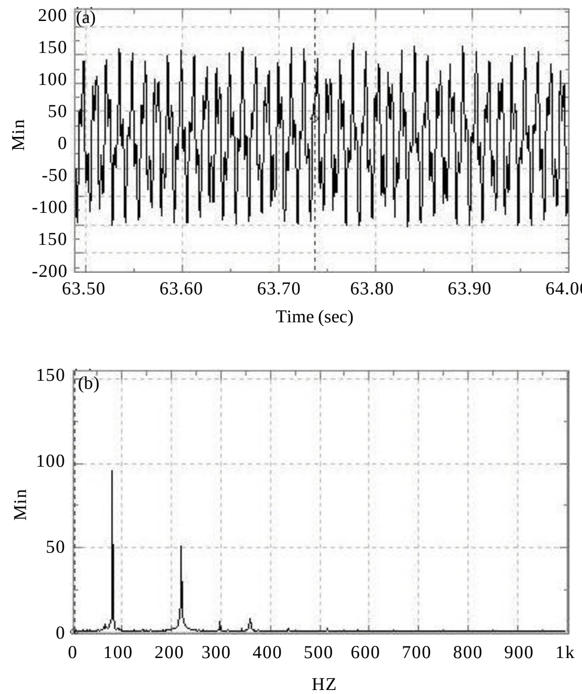

Fig. 8: Time series and power spectrum of input air channel fault

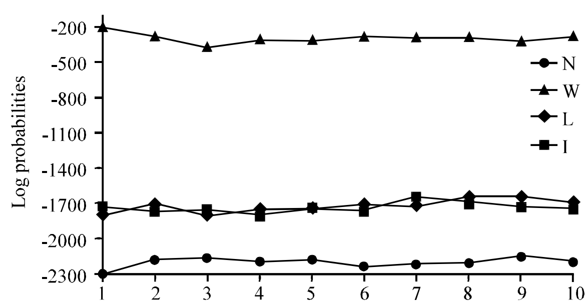

Fig. 9: HMM probabilities under normal condition

Table 1: Result of Vibration recognition by CHMM

Engine stage	Normal	Bolt loose	Output axis whirling	Input air channel
Normal	20	0	0	0
bolt loose	1	18	1	0
output axis whirling	0	0	19	1
input air channel	1	0	0	19

As seen from the above figures and the recognition results, the probabilities of a given data set is largest correspond to the given HMM which represents the condition of the data. The results verified that the proposed method in this study is able to detect and identify the faults of automotive engine in running-up stage (Fig. 7-12).

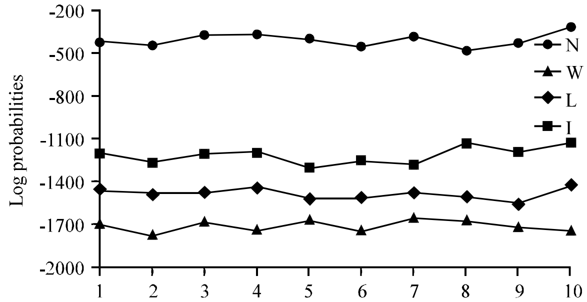

Fig. 10: HMM probabilities under output axis whirling

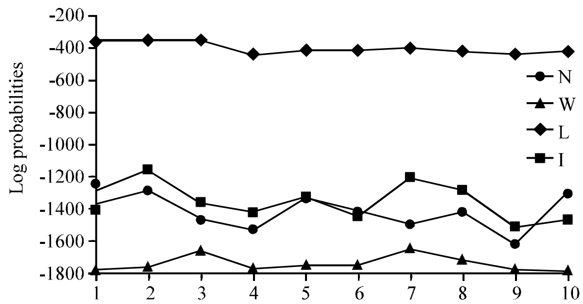

Fig. 11: HMM probabilities under bolt loose

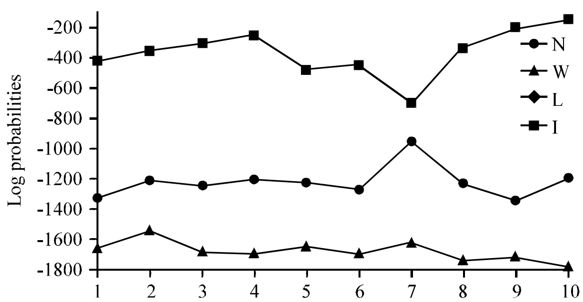

Fig. 12: HMM probabilities under input air channel

CONCLUSION

We introduced the continuous density HMM into the detection and faults diagnosis of automotive engine in running-up stage based on vibration signal. In this method, HMM models were trained to represent various running conditions of engine. These models were test with experimental data collected from the automotive engine. It was shown that this method is executable and effective.

ACKNOWLEDGMENTS

This study is supported by the “Fundamental Research Funds for the Central Universities”, State ethnic Affairs Commision of China and University of Dalian Nationalities talent import fund(20116202).

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