HMM기반 소음분석에 의한 엔진고장 진단기법

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Engine Fault Diagnosis Using Sound Source Analysis Based on Hidden Markov Model

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Abstract

The Most Serious Engine Faults Are Those That Occur Within The Engine. Traditional Engine Fault Diagnosis Is Highly Dependent On The Engineer'S Technical Skills And Has A High Failure Rate. Neural Networks And Support Vector Machine Were Proposed For Use In A Diagnosis Model. In This Paper, Noisy Sound From Faulty Engines Was Represented By The Mel Frequency Cepstrum Coefficients, Zero Crossing Rate, Mean Square And Fundamental Frequency Features, Are Used In The Hidden Markov Model For Diagnosis. Our Experimental Results Indicate That The Proposed Method Performs The Diagnosis With A High Accuracy Rate Of About 98% For All Eight Fault Types.

Key Words : Hmm, Engine Fault, Mfcc, Rms, Bayes

Ⅰ. Introduction

Precise diagnose of engine faults has long been required for engine protection and safety, but current diagnosis techniques fledged to satisfy engine users have not produced satisfactory results. Engine products are advancing fast, but the diagnosis technique is not. Technicians have been relying on their experimental adroitness on diagnosing faults. Diverse engine sounds from a variety of vehicle brands might mislead even an experienced technician in identifying faults. This kind of diagnose routine must be replaced with a new sophisticated technique keeping up with IT solution techniques. A remote diagnosis service should be possible at any time and any place.

Industrial systems with higher performance, safety and reliability have increased the need for fault diagnosis with better precision. Precise fault diagnosis has also taken an important role in process monitoring systems. During the last two decades, various sensors have been developed and employed for fault diagnosis systems by monitoring displacement, vibration, dynamic force, acoustic emission, temperature, sound analysis, etc.

The sound signal analysis is widely used for condition monitoring and fault diagnostics because it is a non-contact diagnosis method with effective usability. With the fast technical development in the signal processing area, various schemes based on Neural network[1], Support Vector Machine[2] and fuzzy logic[3], are proposed to diagnosis engine faults. Unfortunately, these methods are not suitable for non-stationary sound signal analysis[4]. In

addition, they are not able to reveal the inherent information of non-stationary sound signals. These methods provide a limited performance when we use a small dataset of sound signals for the learning phase[1-3]. In order to solve these problems we propose to take the HMM for motor engine fault diagnosis. The method uses the HMM model to consider engine startup characteristics. Data representing the engine startup under the nominal conditions are used to train the HMMs and thus, determine the HMM parameters. This is analogous to system identification methods used to develop empirical models based on neural networks.

From each engine sound data bit the nominal HMM model produces log-likelihood values (posterior probabilities) which represent the closeness of the nominal engine represented by HMM to the engine data. In a similar way, HMM models representing the engine startup under various faulty situations can be developed; these are the so-called fault HMM models. We extracted, from sound source, the MFCC feature, the zero crossing rates, the mean square and the fundamental frequency which are then used to build HMM. In our experiment, a set of eight common types of engine faults is used to evaluate the proposed method. They are Eccentricity, angular misalignment, parallel misalignment; Bowed rotor; broken Rotor bar; Faulty bearing; Rotor unbalance; and Phase unbalance. The experimental result indicated that the proposed method shows the high recognition rate of about 98%.

The remainder of this paper is organized as follows. Section II presents the brief technical background about HMM and MFCC features. Section III elaborates on the scheme we propose. Section IV shows our experimental results. Section V proposes further study to incorporate with the IT infrastructure by smartphone applications.

II. Back Ground

2.1 Hidden Markov Model

This section gives a short introduction to HMMs. The reader is referred to Rabiner[5] for more details on HMMs. A hidden Markov model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. A HMM can be considered the simplest dynamic Bayesian network. In simpler Markov models (like a Markov chain), the state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a hidden Markov model, the state is not directly visible, but output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore the sequence of tokens generated by an HMM gives some information about the sequence of states. Note that the adjective 'hidden' refers to the state sequence through which the model passes, not to the parameters of the model; even if the model parameters are known exactly, the model is still 'hidden'.

A hidden Markov model can be considered a generalization of a mixture model where the hidden variables (or latent variables), which control the mixture component to be selected for each observation, are related through a Markov process rather than independent of each other.

Each file from sound source is associated to each HMM model. It should then do some calculations of probability. Indeed, there is a series of observation O, the problem is to find the maximum value of P(M/O) (the probability of event model M generates the series of observations O).
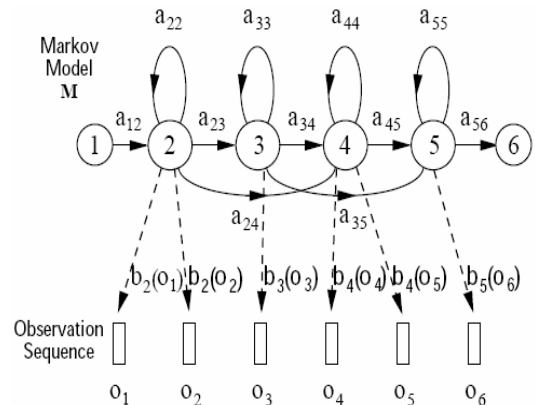

Fig. 1. Hidden Markov Model

The Bayes formula

(1) In sound signal processing, the HMMs used are the left-right type. We advance always right (or one loops itself) and the model is a straight chain of states. The initial probabilities are fixed. We have a number of mathematical properties related to the facts that always makes a transition and that always gets a comment. It is, however, raises two crucial issues:

- Recognition: Given a model and observations as to determine the optimal path according to a suitable criterion.
- Learning: Given labeled examples, how to build HMM models and more specifically how to determine the initial probabilities of transition and observation. It is a first naive method to solve the probability of recognition.

  Suppose we have models with N states and N observations, we can easily assess the likelihood of each model. If multiple paths are possible, we calculate a max on different paths for each model and between different models. For N states and T observations, it has complexity O (TNT).

  To apply the hidden Markov model in the recognition of the sound source, we have to solve three problems:

- First problem - Probability observation sequence: We have an observation sequence and model is given. What is the probability for the controller characterized by the parameters $P(O|\lambda)$
- Second problem - Recognition: There is sequence of observation sequence with a model is given. What is the sequence of state the most probable that produced
- Third problem – Learning: Given the observation sequence and a space of models found by varying the model parameters, what is the best model?

2.2 Mel-Frequency Cepstrum Coefficient

Firstly, module signal processing performs the sound signal analysis on the short timeslots, of 10 to 30 ms. After this step, the signal is represented by acoustic parameter vectors that can discriminate different sound sources, which reduces the amount of information and redundancy.

Actually, our ear is sensitive to frequencies of the sound signal and our hearing is linear with low frequencies (below 1000 Hz) and logarithmic with high frequencies (above 1000 Hz). So batteries triangular filters are varied linearly with low and high frequencies with logarithmic frequencies are used to set the tone. They help us to reduce the amount of information needed to analyze the sound signal. Fig. 2 presents scheme for calculating MFCC coefficients.

There are three main steps in MFCC process[6]:

► Take the Fourier transform (FFT) of (a windowed excerpt of) the input sound signal x[n] we obtain the spectrum of the sound signal X[k].

► Map the powers of the spectrum obtained above onto the mel scale, using triangular overlapping windows.

► Take the logs of the powers at each of the mel frequencies.

► Take the discrete cosine transform of the list of mel log powers, as if it were a signal.
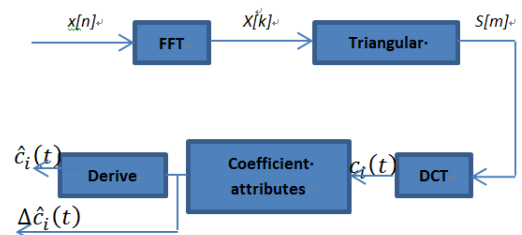
► The MFCCs are the amplitudes of the resulting spectrum.

Fig. 2. Mel-Frequency Cepstrum Coefficient

Ⅲ. Proposed Method

In this section, we propose a system model to detect the engine fault from sound source. The general model is shown in Fig. 3.

Structure of our proposed fault diagnosis system from sound source is shown in the following figure:

Signals of engine failures sound are recorded to files; the first stage is to extracting sound signals
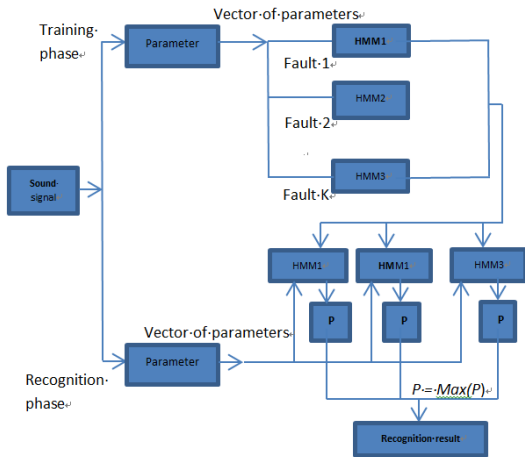
Fig. 3. System structure recognition engine failures

into features (parameters).

Feature extraction phase:

The sound signal is processed with a pre-emphasis filter then ignored the silence part. The filter function is

After that, the sound signal is divided into frames with length from 20 ‑ 30ms. Each frame is multiplied with Hamming window to ensure the continuous of whole signal.

$$w(n) = 0.5 - 0.5\cos\left(\frac{2\pi n}{N-1}\right) \quad (2)$$

The output of this stage is a set of parameter vectors $X = \{X(k)\}$ with $X(k)= \{x1,x2,..xN\}$. Each parameter vector has N dimensions. In this case, we have:

- The number of coefficients is 13 MFCCs
- The number of dynamic parameters (13 parameters derived first order, 13 parameters derived second order)
- A coefficient of energy
- RMS coefficient
- A coefficient of zero crossing rate
- A coefficient of variation of the fundamental frequency

The method to extract MFCCs parameters is described in the previous section.

The zero crossing rate is calculated as follow:

$$ZCR = \frac{1}{n}\sum_{i=2}^{N}|sign(x(n)) - sign(x(n-1))| \quad (3)$$

$$RMS \cdot coefficient \cdot RMS = \sqrt{\frac{\sum_{n=1}^{N}x_n^2}{N}} \quad (4)$$

Coefficient of variation of the fundamental frequency

$$F_{0v} = F_{0\max} - F_{0\min} \quad (5)$$

In the diagram, we can find that the process of recognition of the sound source consists of two phases. This is the learning phase and the recognition phase:

Learning phase:

The set of parameters is used for building of HMMs. In recognition system engine failures using hidden Markov model, each engine failure is represented by an HMM, the parameters of this failure are used to train the corresponding HMM. In fact, the training process is the process of estimating the parameters to obtain the maximum probability $P(O|\lambda)$. This process is performed repeatedly until the difference between two probability $P(O|\lambda)$ has reached a threshold. The provided threshold is calculated based on the number of repetitions following a specified limit.

Recognition phase

The set of parameters is used as the input all HMM models and these models are trained in the previous learning phase. Using the second problem among three problems hidden Markov model, we can easily calculate the corresponding observation probabilities: P1...PK. selecting the probability which is the largest, for example, Pi, then the recognized fault is that the probability Pi represented.

Ⅳ. Experiment

In our experiments, we consider eight states of the activity of engine failure including:

- amis ‑ angular misalignment

- br – bowed rotor shaft
- brb – broken rotor bar
- fbo－faulty bearing (out race)
- mun – rotor unbalance
- nor – normal motor
- pmis – parallel misalignment
- pun – phase unbalance

In figure 3, we show some pictures of engine failure cases.

Detail description of faulty induction motors is defined in table 1.

In figure 4, we represent the wave form of sound signal from each state of engine failure.

Experiment setup

We setup the system to implement the experiment as figure 5. Each experiment is measured twenty times under full-load condition.

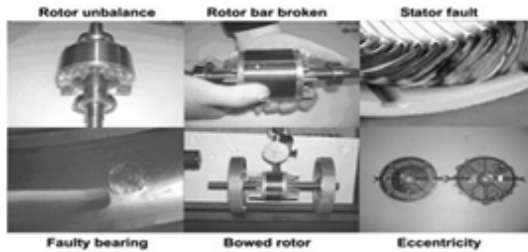The parameters of system are configured as follow:

Fig. 4. Some pictures of engine failures

Table 1. Failure description

| Failure Condition	Description fault	Other
Broken rotor bars	Number of broken bars: 12	Total number of 34 bars
Bowed rotor	Maximum bowed shaft deflection: 0.075 mm	Air-gap: 0.25 mm
Faulty bearing	A spalling on outer raceway	
Rotor unbalance	Unbalance mass on the rotor: 8.4g	
Phase unbalance	Add resistance on one phase	8.4
Eccentricity	Parallel and angular misalignments	Adjusting the bearing pedestal
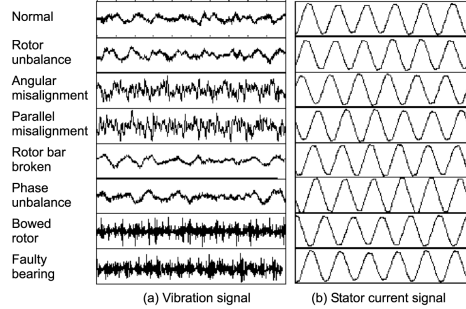
Fig. 5. The signal states of the activity of motor

a1~a3 vibration signal (acceleration)
maximum frequency : 8000kHz
sample number : 16384uh
time: 2.1333 s

The recognition system failures motor is installed well with relative accuracy. This justified the correction of the theory and the effectiveness of hidden Markov model in recognition of the sound source.

The detail of obtained recognition rate is presented in table 2. The preliminary results shown that, exception the unbalance status (phase and rotor) had a lower accuracy rate ($\approx 92 – 93\%$), all other got a very high recognition rate (100%).

We also implemented the fault diagnosis process with neural network[1], SVM[2] for comparison. The result is shown in table 3. The comparison result indicated that our method provides a better result than the NN and SVM method (considering in case of number of files for learning phase is small). In

Fig. 6. Experiment setup.

Table 2. Recognition result

Failure type	Number of files for learning phase	Number of files for recognition phase	Accuracy
Amis	6	13	100%
Br	6	13	100%
Brb	6	14	100%
Fbo	6	13	100%
Mun	6	13	92%
Nor	6	13	100%
Pmis	6	13	100%
Pun	6	30	93%

Table 3. Comparison result

Failure type	NN	SVM	HMM
Amis	96	98	100%
Br	95	98	100%
Brb	97	97	100%
Fbo	94	96	100%
Mun	90	91	92%
Nor	96	97	100%
Pmis	95	95	100%
Pun	90	91	93%

this experiment, we kept all number of files in the learning and recognition phase the same as in the previous experiment.

V. Conclusion

In this paper, we elaborate our method which diagnoses engine failure from sound source. We set up the test environment and implemented the algorithm with S/W. Our experimental results indicated that our method outperformed other methods such as NN and SVM in the recognition rate. The proposed system can recognize 8 different engine failures. The Hidden Markov model has been proved to be efficient in fault recognition of the sound source. However, in further research, the engine fault diagnosis system from sound source needs more complex functions such as: Recognition of most of types of sound sources; Identify in real time, recognition within a noisy environment.

It is difficult to solve these problems above, because it relates to several areas. To deal with these challenges, we can develop the system in some directions: Building module filtering noise and spurious signals; divide sound sources into segments that have similar characteristics then research the characteristics of these segments.

The quick growth of smartphone use in recent years is creating a demand for applications. Based on the obtained result, we propose future work to apply our implementation on the Android smartphone. A set of induction motors tested both normal and faulty, to analyze sound signals recorded with a smartphone. Then, recorded data is analyzed by our Android application to identify healthy and faulty emissions status.

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