ABSTRACT

It's important to understand the dynamic behavior of a structure under operating condition from the viewpoint of vibration shapes of a structure on well excited frequency components and accurate identification of amplitude on each point of a structure. Operating Deflection Shapes (ODSs) can be defined for nonlinear and non-stationary structural motion. ODSs provide very useful information for understanding and evaluating the absolute dynamic behavior of a machine, component or an entire structure. In this study, we use adaptive modal parameter identification method to identify ODSs. The method we use in this study is to perform condition monitoring based on ODSs and diagnosis by changing modal characteristics. We confirm the effectiveness this method by simulation and experiment. It is applied for a rotating machinery with an overhung rotor.

1. INTRODUCTION

In recent years, many different procedures suitable for monitoring and diagnosis of machinery have been developed. These new tools make it possible to perform sophisticated damage detectors that reveal the condition of machinery. The diagnosis system will provide valuable information about the state of the machine.

In-operation damage monitoring and diagnostics of vibrating structures is a useful complement to more classical monitoring techniques. For in-operation monitoring, structures are at work, excitation is not measured and is provided by the environment so it is generally non-stationary. Examples are: offshore structures subject to swell; rotating machinery subject to both rotation effects due to imperfect load balancing, and frictions or steam turbulence; wings or structures of aircraft during flight; rolling stock, etc. Therefore it is hopeful that the diagnosis method that diagnose the normality of the entire structure from the change of modal characteristics by using measured vibration data in operating condition.

ODSs [1] have the advantage that provide an absolute quantity of an amplitude at each point of a structure on well excited frequency components under operating condition and also clear nonlinear and nonstationary structural motion. For identifying ODSs, we use adaptive modal parameter identification method [2]. This method specify frequency components only from multiple responses of a structure under operating condition and can fastly and adaptively identify the physical quantity of an amplitude on well excited frequency components at each measurement point.

We use this method that perform condition monitoring [3] based on ODSs and diagnosis by changing modal characteristics. In order to prove the effectiveness of the method for time varying signals, we demonstrate its performance on artificially generated responses of a rotating machinery with an overhang rotor system and show the effectiveness of this method with practically acquired data.
2. THEORY

Adaptive Modal Parameter Identification Method used in this study identify by using multi point response. This method can identify the ODSs adaptively for time-varying systems by using the URV Decomposition (URVD) \[4\]. This is able to decompose the deformation of a structure under operating condition into the underlying superposition of well excited frequency components. This is a new type of subspace method which can be realized if only you once calculate the two-sided orthogonal decomposition.

Generally let us assume that the measured response is decomposed into the super position of many cisoids. To simplify the data model, following assumption is applied. Dynamic characteristics of the structure are unchanging in frequency band, and the amplitude of frequency component gradually change with time changing.

The amplitude at the arbitrary point \(i\) on the structure at time \(kr\) is represented as \(y_i(k)\). The amplitude \(y(k)\) is given by equation (1).

\[
y_i(k) = \sum_{r=1}^{d} a_{ir}(k) \exp(s_r k \tau) + n_i(k)
\]  

(1)

Where \(r\) is a sampling interval, \(d\) is a number of excited frequency components, \(a\) is a \(r\) th signal's complex amplitude of \(i\) th sensor, \(s_r\) is complex consisted of \(r\) th signal's frequency and damping, \(n_i(k)\) is an observation noise of \(i\) th sensor and it is a Gaussian white noise with unknown variance and zero-mean. Kitagawa \[5\] suggests signal's assumption is applied. Where \(j\) represents imaginary number and \((\cdot)^*\) is used to denote Hermitian conjugate. Sampling interval \(\tau\) was set to 0.002[s]. We used Gaussian white complex noise \(n_i(k)\) and make it change with S/N ratio which use the variance of signal and noise. These time-series are supposed displacement response acquired at five measurement point. We used exponential windowing with a forgetting factor \(\gamma\) =0.99. The time shift \(\tau\) was set to 1.

This method identify by using the basis of row space. URVD was developed to calculate recursively the basis vector of row space. So using URVD is the most suitable to this method. Assuming that we already have a URVD of \(Z\) from previous time. To discount the old data, we adopt exponential windowing which uses forgetting factor \(\gamma\). Let the URVD of \(Z\) from current time be equation (4).

\[
[\gamma Z \; z] = URV^T
\]  

(4)

Where \(Z\) is the incoming row of \(Z\), \(U\) and \(V\) are orthogonal matrix and \(R\) is upper triangular matrix which contain signal space in front and noise space in back. In the URVD, the elements of \(R\) and \(V\) are generally stored and updated, but \(U\) is never constructed in order to reduce the computational cost. By using these information, this method adaptively identify well excited frequency components and the ODSs of each frequency component.

3. NUMERICAL EXAMPLE

The algorithm was coded using MATLAB script files. The measurement data has often much noise under operating condition. We present a simulation result to prove the adaptability of this method for these data by using artificially generated time series.

3.1 SIMULATION CONDITION

We used artificially generated time series, which were generated by equation (5) with \(i=1, \ldots, 5\).

\[
y_i(k) = \sum_{r=1}^{d} [\exp(j2\pi ri/5) \exp(s_r k \tau) \\
+ (\exp(j2\pi i/5)\exp(s_r k \tau)] + n_i(k)
\]  

(5)

Where \(j\) represents imaginary number and \((\cdot)^*\) is used to denote Hermitian conjugate. Sampling interval \(\tau\) was set to 0.002[s]. We used Gaussian white complex noise \(n_i(k)\) and make it change with S/N ratio which use the variance of signal and noise. These time-series are supposed displacement response acquired at five measurement point. We used exponential windowing with a forgetting factor \(\gamma\) =0.99. The time shift \(\tau\) was set to 1.

3.2 THE INFLUENCE OF THE NOISE

We made the data by using equation (5) which only the signal of 10[Hz] existed and the length of sampled data \(k\) was set to 500[Step]. Observation noise was added to this
data, then S/N ratio is made to change from 40[dB] to 2[dB]. This method was applied to these data. In order to evaluate the error of identified frequency, we calculated the error by using equation (6), then evaluated the mean value.

\[
Error[\%] = \frac{(Estimated\ Value) - (True\ Value)}{True\ Value}
\] (6)

Estimation error of frequency was shown in Fig.1 when observation error was made to change. From Fig.1 it knows as noise increases, the error increases, too. The error on S/N ratio 2[dB] is approximately 7[\%]. This fact shows it is successful in the reduction of the noise.

![Fig.1 Estimation error of frequency](image)

In order to prove the content of noise reduction in this simulation, the response at point z = 1 which observation noise which S/N ratio is 2[dB] is added to is shown in Fig.2(a). Fig.2(b) shows the result that estimated value calculated by using this method was compared with true value which the observation noise was not added. The noise in estimated value shown in Fig.2(b) is reduced compared with the noise shown in Fig.2(a), and the estimated value approaches the true value. This result was the same as to the response in four measurement points. It is proved this method shows effect against the reduction of the noise through this simulation.

![Fig.2 Estimation of displacement (i=1)](image)

**3.3 THE TRACKING ABILITY FOR TIME VARIANT SIGNAL**

In order to prove tracking ability of this method for time variant signal, we made the data that 5[Hz] is raised in 1[s] for 10 seconds. 10[dB] observation noise was added to this data, then this method was applied. Identified frequency component at each time was shown in Fig.3. This method began to identify from approximately 0.4[s] in Fig.3. This can be thought it to be a cause that time should be necessary this method to form the signal subspace and estimate rank. Fig.3 indicate that this method can excellently track time variant signal though there is some dispersion through the whole.

![Fig.3 Tracking ability for time variant signal](image)

**4. EXPERIMENT**

In this study, the effect of the proposed adaptive method to identify ODSs is evaluated in an experiment employing a rotating machinery model with an overhung rotor.

**4.1 EXPERIMENTAL APPARATUS**

The experimental apparatus is shown in Fig.4. The displacement responses of rotating shaft were measured on the point A to E shown in Fig.4. The displacement sensor
used in this measurement was eddy current type.

![Diagram of experimental apparatus](image)

**Fig.4 Experimental apparatus**

### 4.2 EXPERIMENTAL PROCEDURE

We perform an experiment under normal condition and the following three abnormal conditions; the critical speed condition, the unbalance condition and the partly loosed condition. The critical speed condition means that the motor on the experimental apparatus was rotated at approximately the critical speed of rotating shaft. The critical speed was identified by using tracking analysis in advance. The unbalance condition means that a bolt with a nut (M8 X 30) was installed in one hole out of symmetrically bored eight holes on the rotor which was located in the end of this shaft. The partly loosed condition means the condition that the screw which fixed the motor was loosed.

### 4.3 EXPERIMENTAL RESULT AND CONSIDERATION

The rated frequency of the motor was fixed 75[Hz] under the normal, unbalance and partly loosed condition. On the other hand, the rated frequency of the motor was 15[Hz] under the critical speed condition. In rotating machinery, it's natural that the rotating frequency which the rotating machinery works is well excited. Therefore, the rotating frequency may be identified as one of well excited frequency by using this identification method. The estimation result of well excited frequency under the normal condition and the other three abnormal conditions are respectively shown in Fig.5 to Fig.8. It is confirmed that the rotating frequency was identified as well excited frequency components in Fig.5 to Fig.8. In Fig.5, 150[Hz] component is identified except for the rated frequency 75[Hz] under the normal condition, too. This fact is mainly because $n$th order of the rotating frequency is generally excited in rotating machinery. Where $n$ is integer.

In Fig.8, Estimated values of frequency are dispersedly plotted between 80[Hz] and 100[Hz] along with the step number. This result give us useful information that the machine works under abnormal condition.

Then we consider about ODSs under the normal condition. ODSs acquired by using displacement response data is shown in Fig.9. ODSs calculated by applying this identification method for displacement response data are shown in Fig.10(a) and Fig.10(b) for each component. It is apparently confirmed that the amount of their two identified ODSs corresponds to the result shown in Fig.9 (not shown in figure).

Then the identified ODSs under each abnormal condition, namely the critical speed condition, the unbalance condition and the partly loosed condition are respectively shown in Fig.11 to Fig.13. From Fig.11, it can be confirmed that a remarkable vibration occurs around the rotor by comparing with the normal condition. From this result, it is found an unbalance vibration on the rotating machinery with an overhung rotor occurs. It is confirmed that vibration under the unbalance condition is drastic than the vibration under the critical speed condition. A certain amount of vibration is appeared around the motor under the partly loosed condition in Fig.13. Consequently it is proved that condition monitoring with ODSs is successful under each condition by using this identification method.

![Graph of estimated frequency](image)

**Fig.5 Estimated frequency (The normal condition)**

![Graph of estimated frequency](image)

**Fig.6 Estimated frequency (The critical speed condition)**
Fig. 7  Estimated frequency (The unbalance condition)

Fig. 8  Estimated frequency (partly loosed condition)

Fig. 9  ODSs using displacement sensor (The normal condition)

(a) Identified ODSs on 1st main frequency (The normal condition)

Fig. 10 Identified ODS (The normal condition)

(b) Identified ODSs on 2nd main frequency (The normal condition)

Fig. 11 Identified ODSs (The critical speed condition)

Fig. 12 Identified ODSs (The unbalance condition)
5. CONCLUSION

In order to make a diagnosis of a rotating machinery with an overhung rotor, we propose an adaptive modal parameter identification method which identify the ODSs corresponds to the well excited frequencies.

At first, we proved the effectiveness of this method for the signal including noise and time-varying signal in simulation stage. Then we performed the experiment in which a rotating machinery with an overhung rotor is used. We confirm this method can adaptively identify well excited frequency components and ODSs in high precision. Consequently the method we use in this study can perform condition monitoring based on ODSs and diagnose the structure by using information of well excited frequency.

It is however necessary to evaluate this method on experimentally acquired data under non stationary condition.

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7. REFERENCES


