Online damage evaluation of hole-edge crack using guided wave based Hidden Markov Model

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Key words: Structural health monitoring, Time-varying environment, Guided wave, Hidden Markov Model, Damage evaluation.

Abstract

Structural health monitoring based on guided wave plays an important role in the damage evaluation of practical application. However, the damage evaluation under time-varying environments which introduces undesired uncertainties to guided wave features is difficult to achieve reliably. In this paper, an approach of guided wave based Hidden Markov Model (HMM) method is proposed to improve the reliability of damage evaluation under time-varying environment. With this method, a left-right continuous HMM which is composed of several hidden states is trained firstly based on the time-varying affected guided wave features of different damage states. Each hidden state of HMM represents a damage state of a monitored structure under time-varying environment. Then a maximum average posterior probability based on the HMM can be obtained to evaluate the damage when a new guided wave feature is obtained during an on-line damage process. Finally, the method performance is validated by monitoring the hole-edge crack of an aluminum tensile specimen under fatigue load condition and result shows that the reliability of damage state evaluation is improved.

1 INTRODUCTION

The reliable damage evaluation under uncertainties due to time-varying environmental and operational conditions is one of the key challenges of practical engineering applications of structural health monitoring (SHM). The time-varying environment, which contains temperature, load, structural boundary condition and etc., makes it difficult to analyze the changes of guided wave signal which has a widespread use for small damage in SHM. This leads to unreliable evaluations of the structural state [1, 2, 3]. Several approaches have been proposed to address the effects of time-varying environment, such as environmental parameter compensation [4, 5, 6], baseline signal dependency reduction [7, 8] and data normalization [9, 10].

In recent years, probabilistic and statistical models have been reported to deal with the effects of time-varying environment, which are effective tools for characterizing uncertainties of signals, such as Hidden Markov Model (HMM) [11], Gaussian mixture model [12], self-organizing maps [13], and stochastic global model [14]. Among these probabilistic and statistical models, HMM is a powerful probabilistic and statistical modeling tool. It has a strong capability in pattern classification, especially for signals with non-stationary natures and poor repeatability and reproducibility [15, 16]. In the research field of SHM, several researchers have begun to apply the HMM to damage evaluation. Rammohan and Taha carried out an exploratory investigation on damage prognosis using the HMM to model the simulated data of a pre-stressed concrete bridge [17]. Tschöpe and Wolff studied the HMM for damage degree classification on plate-like structures [18]. However, deep research still needs to be further performed to validate the potential of HMM to improve the damage evaluation reliability under time-varying environment.

In this paper, a Guided Wave (GW) based HMM method is proposed to deal with the time-varying problem of damage evaluation. Before evaluating damage state, the parameters of HMM are trained by the measured GW signals from different damage states of structures under time-varying environment using Baum-Welch algorithm. By putting the new monitoring GW signals into the trained HMM, the posterior probabilities of damage states are used to achieve the damage state evaluation. Then a moving average of the posterior probabilities is applied to improve the reliability of the damage state evaluation. Finally, the effectiveness of the proposed method is proved by an experimental validation which is carried on a hole-edge crack monitoring of an aluminum tensile specimen under dynamic load condition.

2 GUIDED WAVE BASED HMM

2.1 Method principle

HMM is a type of probabilistic model introduced by Baum et al. at the end of the 1960s and first applied to speech processing. It is composed of two layer stochastic processes which are respectively the stochastic transition between hidden states and the stochastic probability from the states to the observations [19]. The monitoring data collected during the damage propagation can be divided into several groups which are corresponding to different damage states. Due to the uncertainties under time-varying environment, these data of adjacent damage states usually overlap with poor reproducibility. Hence a HMM model can be used for damage evaluation where the hidden states of HMM represent different damage states and the observations are the monitoring data. Since the damage propagation processes are often irreversible in reality, a left-right HMM is used in this paper. Moreover, damage propagation can change the continuity of the structural medium which affects the features of GW signal. The damage index extracted from the GW signals in time domain, frequency domain, and time-frequency domain is sensitive to small damages.

Based on the above principle, the implementation process of the proposed GW based HMM damage evaluation method is shown in Fig. 1. It includes two parts, severally off-line training and on-line damage evaluation.

During the off-line training, the GW signals of different damage states under time-varying environment are collected. The damage indexes are extracted from those signals and taken as the input to train the parameters of HMM model which is used for the on-line damage evaluation.

In the part of the on-line damage evaluation, the goal is to assess the optimal damage state of the monitoring structure based on the collected GW signals. Using the trained HMM, the posterior probability of each damage state can be calculated. Besides, considering the stochastic performance of the changing environment which can alter the damage indexes in a short interval, a moving average of the posterior probabilities is used to reduce the effects of short-term time-varying environment and provide a more reliable damage evaluation. Finally, by selecting the max average posterior probability, the most possible state of the damage can be estimated.

Two typical damage indexes are obtained directly from the monitoring signal without comparing with the baseline signal which is hard to choose under time-varying environment. They are employed to indicate the signal variations in the paper. The first damage index (DI_1) is the signal energy, which is defined as $DI_1=\int M^2(x)dx$, where M(x) represents the amplitude of the collected GW signal. The second one DI_2 is the amplitude of peak frequency and defined as $DI_2=\max(|M(f)|)$, where M(f) is the Fourier transform of M(x).

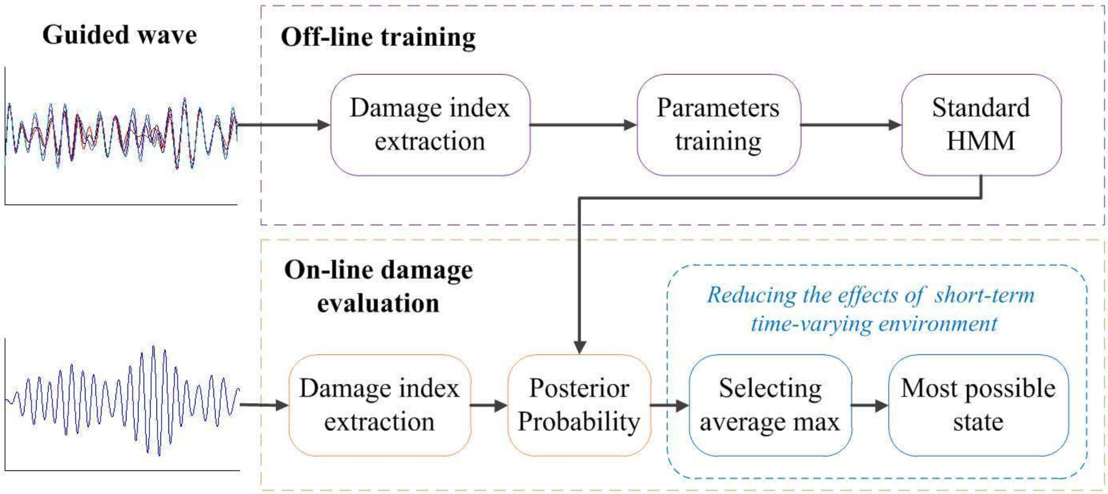


Figure 1: The process of HMM for damage evaluation.

2.2 HMM parameter training

HMM model can be represented by a compact notation $\delta=(\pi, A, B)$:

(1) M: Number of hidden states.

(2) π: the initial state distribution vector $\pi=P(s_1=i)$.

(3) A: the state-transition probability matrix $A=[a_{ij}]$, where $a_{ij}=P(s_{t+1}=j|s_t=i)$.

(4) B: State-dependent observation density $B=\{b_i(\mathbf{v}_t)\}$, where $b_i(\mathbf{v}_t)=P(\mathbf{v}_t|s_t=i)$, and $\mathbf{V}=\{\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_T\}$ representing the observation sequence.

The observations of damage extension usually are multidimensional continuous signals in real structure. Hence continuous HMM with Gaussian Mixture Model based on unsupervised learning to model the distribution of the observations can reduce the loss of effective data. The elements of B are given by Eq. (1):

$$b_i(\mathbf{v}_t)=\Sigma_l(\boldsymbol{\omega}_{i,l}\xi(\mathbf{v}_t, \boldsymbol{\mu}_{i,l}, \boldsymbol{\Sigma}_{i,l})) \quad (1)$$

where $\boldsymbol{\mu}_{i,l}$, $\boldsymbol{\Sigma}_{i,l}$, $\boldsymbol{\omega}_{i,l}$ are the mean vector, the covariance matrix, and the mixture weight of the l-th Gaussian component in structural damage state i.

For the tasks of damage evaluation, the parameters of HMM model, $\delta=(\pi, A, B)$, need to be adjust to maximize $P(\mathbf{V}|\delta)$, which is the probability of an observation sequence $\mathbf{V}$ given the model δ, as defined in Eq. (2)

$$\delta_m = \text{argmax } P(\mathbf{V}|\delta) \tag{2}$$

The Baum–Welch algorithm is used for the parameter training of HMM. It is a special case of the expectation-maximization (EM) algorithm and maximizes the log-likelihood of $P(\mathbf{V}|\delta)$ of the training data iteratively. Before the iteration, parameters of HMM need to be initialized. The iteration will be stopped if the convergence criterion shown in Eq. (3) is satisfied or the maximum iteration number n_{max} is reached

$$\log(P(\mathbf{V}|\delta_{n+1}))\text{-}\log(P(\mathbf{V}|\delta_n))<\varepsilon \tag{3}$$

The forward-backward algorithm is used to computer the $P(\mathbf{V}|\delta)$ based on the trained model and the input observation $\mathbf{V}=\{\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_T\}$.

2.3 Damage evaluation method

After the parameter training of HMM, the HMM is used to recognize the most possible damage state of the structures s_t by making the new measured observation sequence $\mathbf{V}=\{\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_t\}$ as the input of the trained HMM model to obtain the posterior probabilities of the sequence corresponding to each states. The posterior probability defined as $P_{i,t}=P(s_t=i|\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_t, \delta_m)$ can be calculated by the Bayes' rule, shown in Eq. (4).

$$P_{i,t}=(P(\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_t, s_t=i|\delta_m))/(P(\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_t|\delta_m)) \tag{4}$$

Once the posterior probability of the observation mapping to each damage state computed, the most possible damage state s_t can be determined preliminarily by choosing the state with the maximum posterior probability at the time t. To reduce the effects of short-term time-varying environment and achieve a more reliable estimation, a moving average of posterior probability $(P_{i,t})_a$ of the damage state i is defined using Eq. (5)

$$(P_{i,t})_a=(P_{i,t-k+1}+\ldots+P_{i,t-1}+P_{i,t})/k \tag{5}$$

where $P_{i,t}$ is the posterior probability calculated by Eq. (4), and k is the average span which depends on the monitored damage and the time-varying environment. The trend of damage propagation can be obtained using the average posterior probabilities $(P_{i,t})_a$. Reliable damage evaluation is realized by maximizing the $(P_{i,t})_a$ to determine the most possible damage state $(s_t)_a$ as

$$(s_t)_a=\text{argmax}[(P_{i,t})_a] \tag{6}$$

3 METHOD VALIDATION

3.1 Validation setup

To prove the effectiveness of the proposed method, a validation experiment is performed on a hole-edge crack specimen under dynamic load condition. Besides, static load is applied on the specimen corresponding to different crack lengths to testify that the damage indexes proposed in the paper will change with the crack propagation. The whole observation sequence obtained from different damage states of a hole-edge crack specimen under dynamic load condition are classified into two groups equally. One is used for the parameter training of HMM model and another is applied as the input of the trained HMM for evaluating the damage state.

The hole-edge crack specimen in the experiment is made of 2mm thick YL12 aluminum with a 25mm-diameter through hole. A 3mm notch at the edge of the through hole is made to control the crack propagation direction. Two PZTs with a distance of 80mm are placed on the sample. PZT 1 is used as actuator while PZT 2 as sensor. For evaluating the crack length, a series of lines with 2mm interval are marked perpendicular to the direction of crack propagation. The dynamic load is applied while the crack expands between two marked lines. When the crack reaches the marked line, the dynamic load is suspended. A tensile load of 5kN is applied instead. A total of 190 signals are collected, which are divided into four groups on behalf of four different damage states of the specimen corresponding to the changes of crack length 0mm, 0-2mm, 2-4mm, 4-6mm under dynamic load condition. 4 monitoring signals under static load are collected, corresponding to crack lengths 0mm, 2mm, 4mm, and 6mm respectively.

A material test system MTS810 is used to apply fatigue load. The dynamic load is a 10Hz sinusoidal tensile load with peak value V_{max}=15kN and valley value V_{min}=1.5kN. The SHM system developed by the authors' group [20] is employed to excite and collect GW signals. A 5-cycle tone-burst signal with the center frequency of 290 kHz and ±10V amplitude is used as the excitation signal.

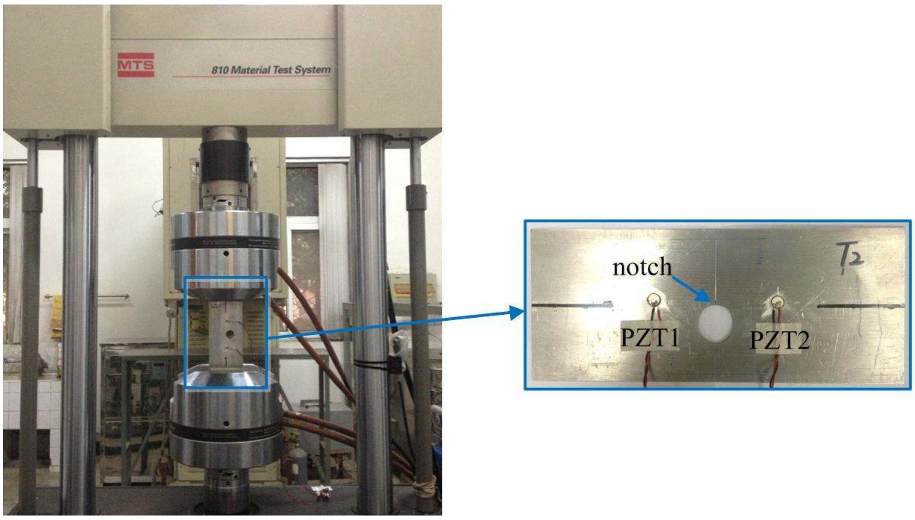
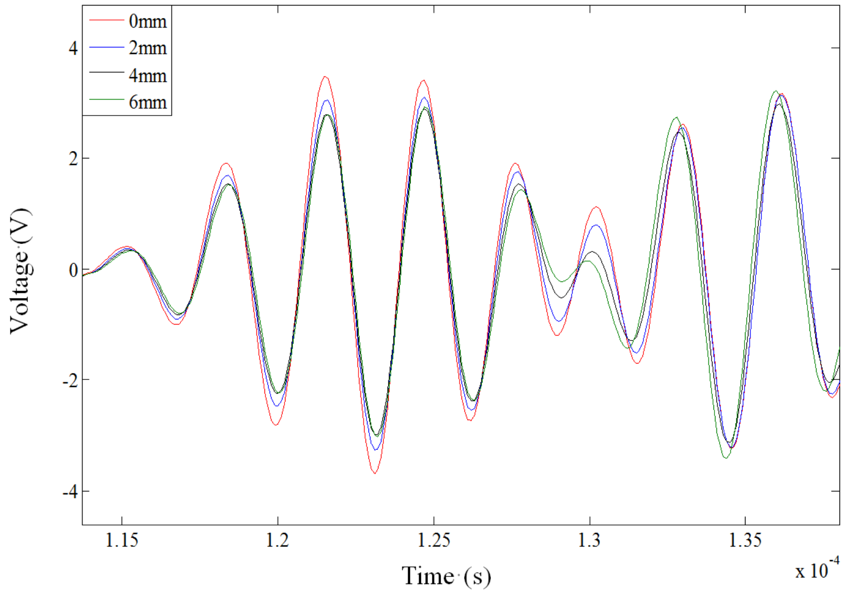


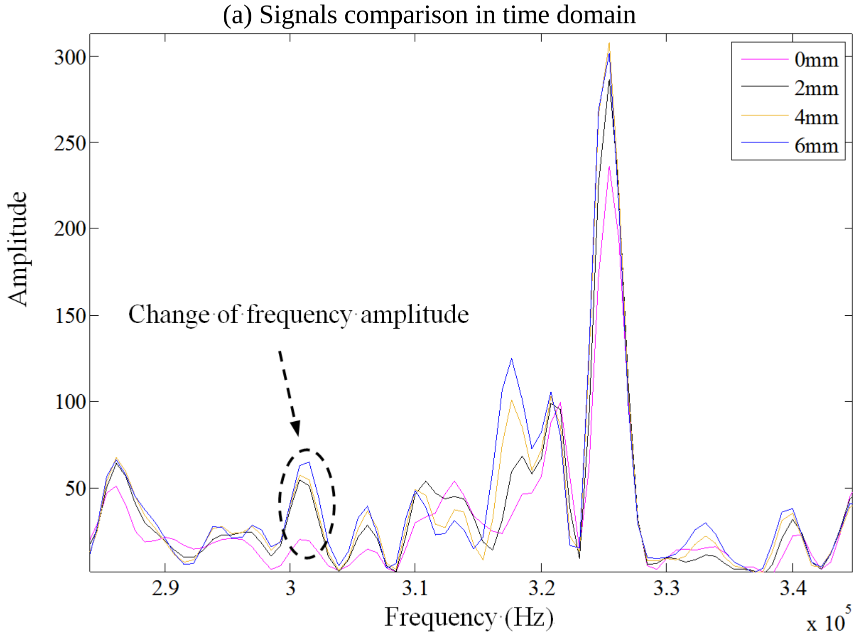
Figure 2: The hole-crack sample.

3.2 GW signals monitoring result

The sample GW signals and their frequency spectrums under static load condition corresponding to different crack lengths are shown in Fig. 3. Then damage indexes are extracted from these signals. Damage index DI_1 is calculated directly from the time domain signal by eliminating the crosstalk part. DI_2 is chosen from the frequency spectrum between $f_1=2.98\times10^5$Hz and $f_2=3.05\times10^5$Hz which is around the peak frequency of 303 kHz. It can be easily found that damage indexes proposed in the paper change with the crack propagation as illustrated in Fig. 4.



(a) Signals comparison in time domain



(b) Signals comparison in frequency domain

Figure 3: Typical signals comparison of different crack lengths under static load.

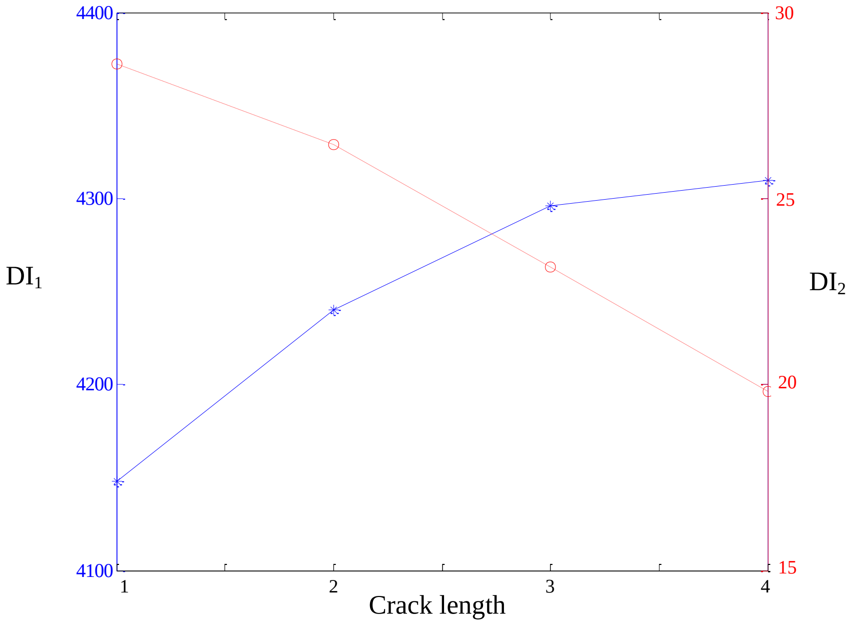


Figure 4: Damage index obtained under static load condition.

Fig. 5 gives out the damage indexes extracted from the signals under dynamic load condition. Because the effect from dynamic load on the GW signals is bigger than that of the crack propagation, it is difficult to distinguish the extension of crack.

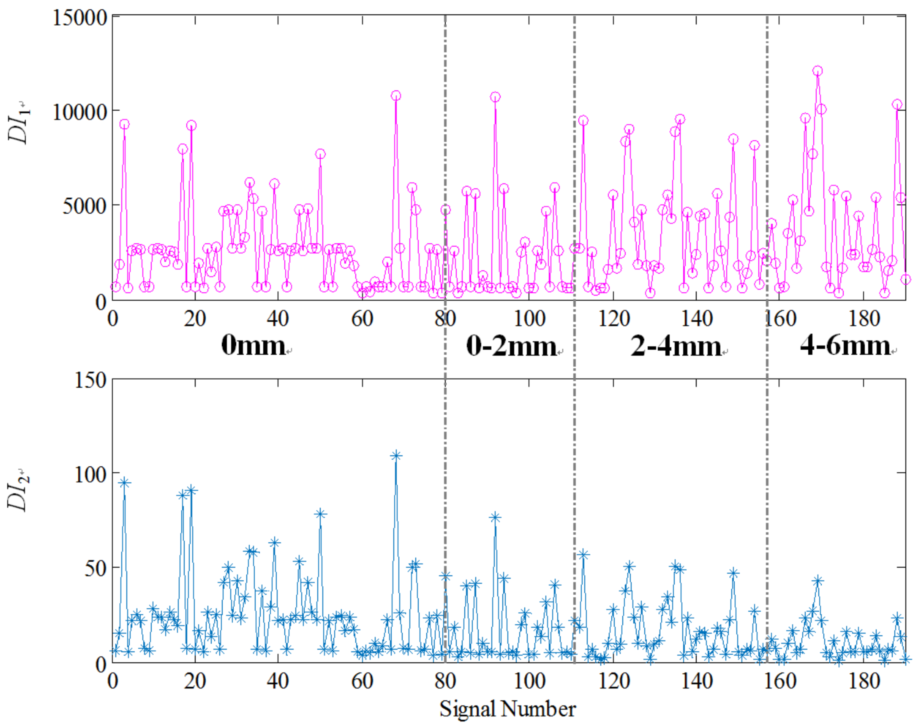


Figure 5: Random variations of the two damage index under dynamic loading condition.

3.3 HMM based crack monitoring results

The 190 measurements obtained under dynamic load condition corresponding to 4 different structural damage states are classified into two groups equally. Each group has 95 observations for training and evaluation respectively. The training dataset of 95 observations $\mathbf{V}_t=\{\mathbf{v}_1,\mathbf{v}_2,\ldots\mathbf{v}_{95}\}$ is used to train a 4-state left-right HMM.

The parameters of the HMM model are initialized as:

$$\pi_0 = [1, 0, 0, 0] \quad A_0 = \begin{bmatrix} 0.9 & 0.1 & & \\ & 0.9 & 0.1 & \\ & & 0.9 & 0.1 \\ & & & 1 \end{bmatrix}$$

Based on the observation density estimation method introduced in Section 2.2, choosing the number of Gaussian components is 2. The $\boldsymbol{\mu}_{i,l}$, $\boldsymbol{\Sigma}_{i,l}$, $\boldsymbol{\omega}_{i,l}$ of the Gaussian Mixture Model for each structural state are initialized based on the training signals. The parameters of the HMM model are adjusted by the Baum–Welch algorithm. The value of convergence criterion ε of Eq. (3) is set to 1×10^{-10}. The maximum iteration number n_{max} is set to 200. The convergence of the log-likelihood value calculated using Baum–Welch algorithm comes to an end after 30 iterations where the change of log-likelihood is less than ε.

Once the HMM model trained, it is used with the remaining 95 observations under dynamic load condition for damage evaluation. The posterior probabilities are calculated as illustrated in Fig. 6 where there are some misjudgments during the damage evaluation.

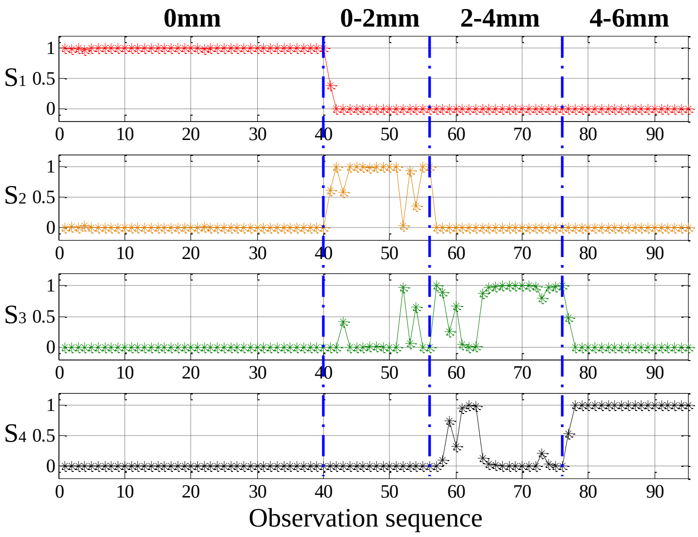


Figure 6: The posterior probabilities based on the proposed method.

A moving average span of 10 based on the experiments is chosen for the $(P_{i,t})_a$. The damage evaluation results by choosing the state corresponding to the maximum $(P_{i,t})_a$ can be obtained as illustrated in Fig. 7. Since the presented method is based on the trend of the damage propagation, the results show that at the transition points of structural states, the evaluation has some delay. The degree of delay depends on the moving average span k, which should be carefully chosen according to real application objects.

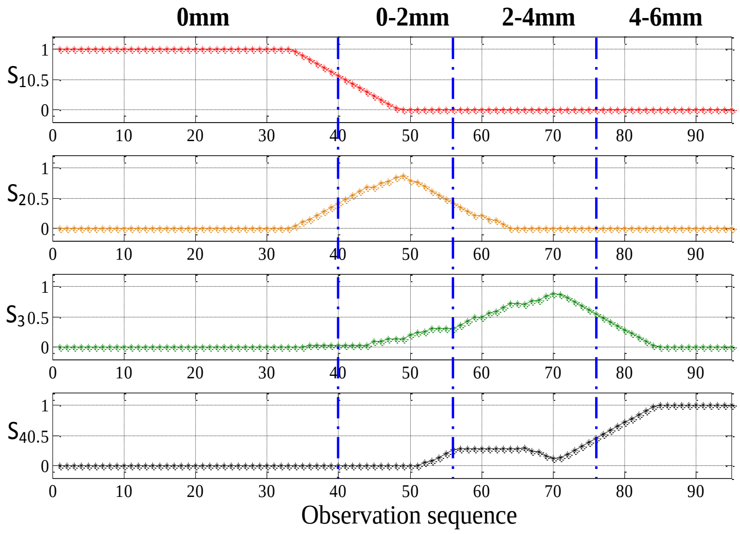


Figure 7: The damage evaluation results.

4 CONCLUSIONS

This paper represents a new damage evaluation method based on HMM and guided wave to reduce the effects of time-varying environment and provide a more reliable damage evaluation. The experiments performed on hole-edge crack of an aluminum tensile specimen under fatigue load condition prove that the proposed HMM method has a good capability for damage assessment under time-varying environment.

5 ACKNOWLEGEMENT

This work is supported by the National Science Fund for Distinguished Young Scholars (Grant No.51225502), the Natural Science Foundation of China (Grant No.51575263), the Qing Lan Project and the Prioritized Academic Program Development of Jiangsu Institutions of Higher Educations.

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