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Technical Note

Markov chain-based mass estimation method for loose part monitoring system and its performance

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ABSTRACT

A loose part monitoring system is used to identify unexpected loose parts in a nuclear reactor vessel or steam generator. It is still necessary for the mass estimation of loose parts, one function of a loose part monitoring system, to develop a new method due to the high estimation error of conventional methods such as Hertz's impact theory and the frequency ratio method. The purpose of this study is to propose a mass estimation method using a Markov decision process and compare its performance with a method using an artificial neural network model proposed in a previous study. First, how to extract feature vectors using discrete cosine transform was explained. Second, Markov chains were designed with codebooks obtained from the feature vector. A 1/8-scaled mockup of the reactor vessel for OPR1000 was employed, and all used signals were obtained by impacting its surface with several solid spherical masses. Next, the performance of mass estimation by the proposed Markov model was compared with that of the artificial neural network model. Finally, it was investigated that the proposed Markov model had matching error below 20% in mass estimation. That was a similar performance to the method using an artificial neural network model and considerably improved in comparison with the conventional methods.

1. Introduction

The purpose of a loose part monitoring system is to monitor whether there are unexpected objects, called loose parts, in a reactor vessel and/or steam generator. Usually, bolts, nuts, and metallic fragments are potential loose parts that can cause interior structural damage. A loose part monitoring system has two major functions: indicating the position of a loose part that may exist in a reactor vessel or steam generator (localization), and estimating its mass (mass estimation) [1].

Several types of localization techniques [1–3] for loose parts have been developed, such as the hyperbola, circle, and triangular intersection methods. In recent years, their performance has considerably been improved by adding signal-processing methods that can grasp the propagating characteristics of a dispersive wave by employing Wigner–Ville distribution [4].

However, mass estimation still needs to be improved in terms of performance to reduce the error in an estimated mass. There are two conventional methods for mass estimation. One is an analytic method based on Hertz's impact theory, which is expressed as follows [5]:

$$T_{contact} = 2.95 \cdot k_h \cdot M^{0.4} \cdot V^{-0.2} \cdot R^{-0.2} = {}^{1.6}\!\Big/_{2f_p}, \tag{1}$$

$$k_h = \left[\frac{15}{16}\left(\frac{1-\nu_1^2}{E_1} + \frac{1-\nu_2^2}{E_2}\right)\right]^{0.4}, \tag{2}$$

where $T_{contact}$ is the impact contact time, M is the mass of an impacting object, V is the velocity of an impacting object, R is the radius of curvature at the contact point, and k_h is a material constant related to Young's modulus (E_1, E_2) and Poisson ratios (ν_1, ν_2) of the plate and impacting object. The third term of Eq. (1) is obtained from the relationship in which the contact time is inversely proportional to the dominant frequency (f_p) of the Lamb wave. When this method is utilized to determine the mass of an object, there is a considerable problem that uncertainty related to three variables, V, R, and f_p, should be solved [6].

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The other is a frequency ratio (FR) method [7] defined as follows:

$$FR = \frac{\int_{1\text{kHz}}^{6\text{kHz}} S(f)df}{\int_{10\text{kHz}}^{15\text{kHz}} S(f)df}, \tag{3}$$

where $S(f)$ is the auto-power spectrum density (APSD) of the impact signal and f is a frequency. It has been determined that the power of the low-frequency band, the numerator of Eq. (3), is subjected to the impact mass and the power of high-frequency band, the denominator, is rarely changed by external excitation because the frequency range is strongly affected by the used sensor's feature [7,8]. A previous study [7] stated that the FR method had an uncertainty or error range for the estimated mass as much as approximately 0.7 decades.

To overcome these problems in the above two conventional methods for mass estimation, artificial neural network (ANN) was employed to estimate the mass of loose parts. ANN has a good theoretical background and performs feature mapping with improved accuracy, and so is typically used in deterministic classification [9]. Figedy and Oksa [10] introduced an ANN model that used the four mean values of APSD in the defined four frequency bands as input variables. Shin et al. [11] also proposed an ANN model that makes use of the coefficients of discrete cosine transform (DCT) on APSD of the impact signal as inputs and showed that the DCT reflected the features of APSD used for the two conventional mass estimation methods. Although the relative error of the ANN model for mass estimation was considerably improved compared with conventional methods, there was a weak point that the ANN model should be wholly retrained when any new loose parts having different masses would be considered.

The purpose of this study is to investigate the performance of the mass estimation method using the Markov decision process instead of the ANN model. The Markov decision process is a mathematical framework for modeling decision making as a Markov model. The Markov model has the advantage that it is easy to add a model for a new event separately from the models for classifying existing events. To this end, first, how to extract feature vectors using DCT was briefly explained. Next, Markov chains were designed with codebooks obtained from the feature vector, which are sometimes called input vectors. A 1/8-scaled mockup of the reactor vessel of OPR1000 was employed as an application example. The dimensions of the mockup are as follows: height 1,750 mm, outer radius of the lower hemisphere 260 mm, and thickness of the lower hemisphere 16 mm. All used signals were obtained by impacting its surface with several solid spherical masses. Finally, mass estimation performance of the proposed Markov chain model was compared with those of the ANN model [11] and two conventional methods by checking the degree of agreement between the real and estimated masses.

2. Feature extraction of impact signals

As already stated, it is well known that the APSD curve of an impact signal is mainly changed in the frequency domain according to the impacting mass. Fig. 1 shows the impact signals according to mass in the time domain and a comparison of their APSD curves in the frequency domain. When an impacting mass is heavy, the main frequency range in which most of the energy exists is narrow and shifted to the low-frequency side; meanwhile, when the mass is light, the main frequency range is wide and shifted to the high-frequency side. In particular, impact strength changes the level of APSD, but its overall shape in the frequency domain is maintained [11]. Two conventional methods also made use of these features to estimate the impacting mass [12].

The basic idea of reflecting the relationship between the APSD of the impact signal and the impacting mass is to determine the small number of factors that can reproduce the APSD curve. Thus, the coefficients of the DCT were introduced as shown in Fig. 2 [11]. After obtaining APSD, a smoothing process was performed to take into account the overall pattern or shape of the APSD curve. DCT is applied to the smoothed data, and if a suitable number of coefficients are selected, the APSD curve can be copied by the inverse DCT with the coefficients. The level difference due to the impact strength is solved by removing the first coefficient of DCT representing the DC offset in level. As a result, the coefficients of DCT could be used as feature vectors that are inputs in event classification.

3. Mass estimation using Markov model

This study employs a Markov model to estimate the impact mass for a loose part monitoring system. The Markov model is a statistical algorithm used for pattern classification, speech recognition, fault diagnosis, etc. It has a mathematically systematic structure, high computational efficiency [13,14], and the distinct advantage of easy extension to the types of objects to be classified or the types of recognizable fault. In this chapter, impact signals

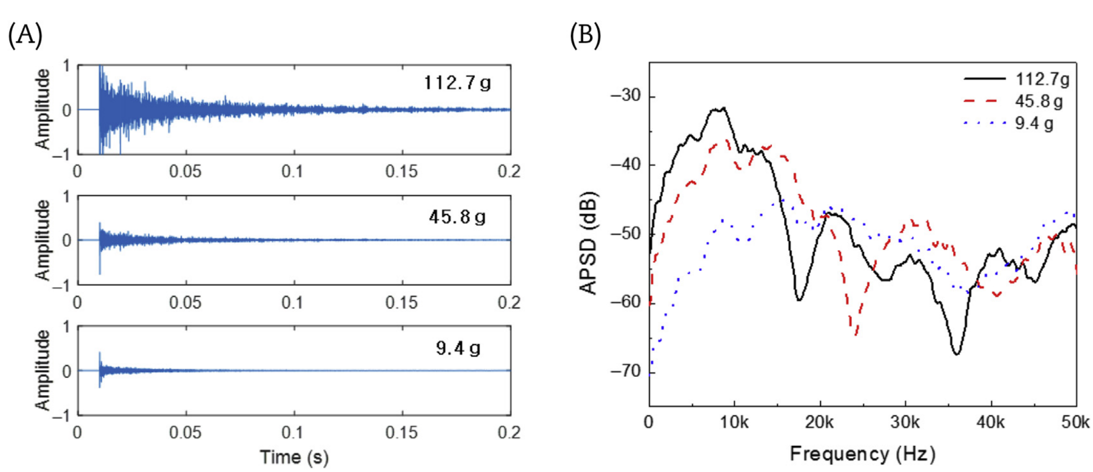

Fig. 1. APSD curves of impact signals. (A) Impact signals of three different masses. (B) Comparison of their APSD curves. APSD, auto-power spectrum density.

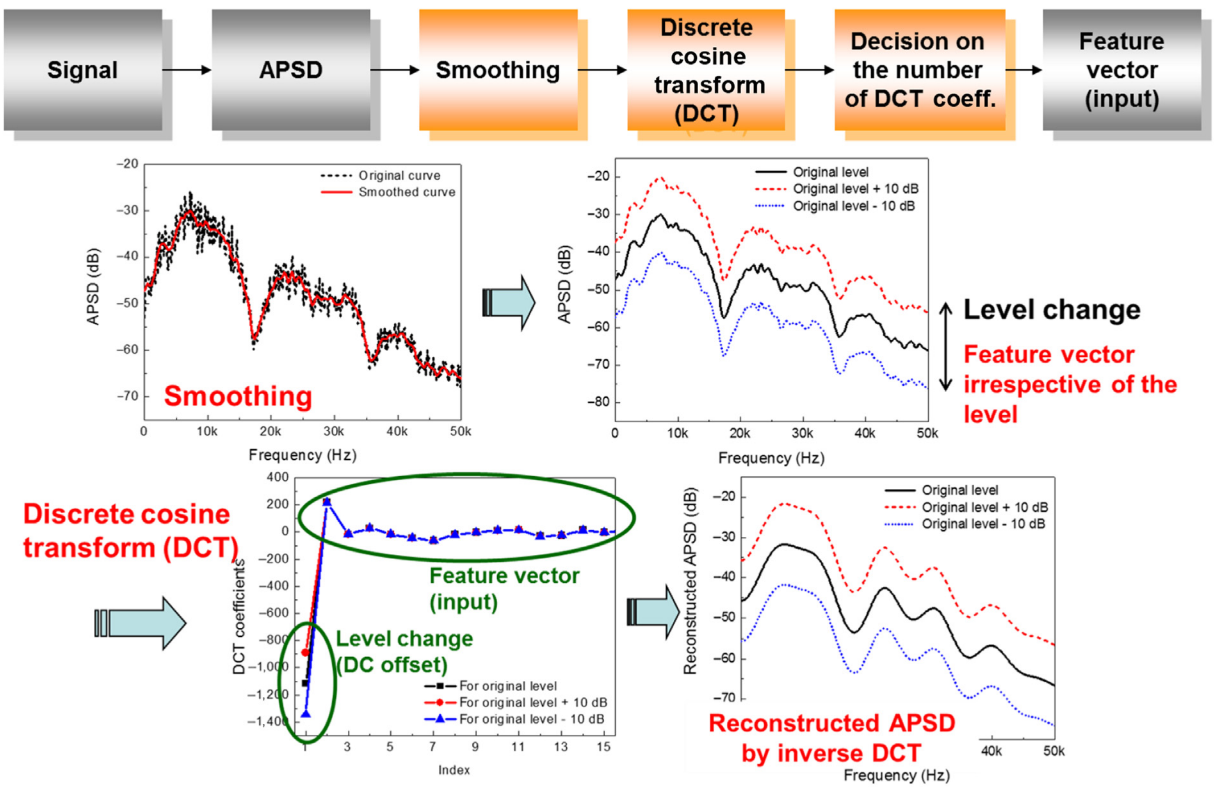

Fig. 2. Procedure for extracting the features of the impact signal by employing discrete cosine transform [11]. APSD, auto-power spectrum density; DCT, discrete cosine transform.

were obtained from a 1/8-scaled mockup of a reactor vessel, and a Markov model for estimating the impact mass was designed using the coefficients of DCT as input variables.

3.1. Impact signals as test samples

A 1/8-scaled mockup of the OPR1000 reactor vessel was employed to get the impact signals. Eight accelerometers were installed in the lower part of the mockup, as shown in Figs. 3A and 3B. Three accelerometers were located at positions that correspond to the actual ones in the real reactor, and the others were positioned arbitrarily. Nine solid spheres of different masses (112.0 g, 68.9 g, 45.8 g, 36.9 g, 29.1 g, 24.7 g, 17.7 g, 9.4 g, and 4.6 g) were collided with the mockup.

To obtain the training data for a model, each sphere was hit at six different points with five different energies, that is, different impact velocities at each impacting point. To get test data, the solid spheres were collided at arbitrary points and with arbitrary energies. As a result, for each accelerometer, 240 impact signals for the training and 99 for the test were obtained.

3.2. Design of the Markov model

The most important aspect of recognizing and classifying events in a problem is finding an optimal input vector that closely represents the features of events. This study employs the coefficients of DCT on the APSD of an impact signal as the input vector. As shown in Fig. 2, it is necessary to determine how many coefficients should be used when reconstructing the pattern of the APSD curve in the 1/8-scaled mockup. Fig. 4A shows the result of comparison between the original APSD curve and the reconstructed curve by the inverse DCT with a finite number of coefficients. As the number of DCT coefficients that are used increases, the process of how the reconstructed curve approximates the original curve improves. In particular, the two curves are nearly identical when using 25 DCT coefficients for the inverse DCT. To check the agreement between the original and reconstructed curves, the mean square error between them was calculated as a function of the number of used coefficients, as shown in Fig. 4B. The mean square error value is converged when more than 13 DCT coefficients were used for approximating the APSD curve. This study used this result to determine that 14 DCT coefficients were sufficient to represent the features of the APSD of the impact signal; therefore, the input vector was composed of 13 DCT coefficients, excluding the first.

A Markov model is a stochastic process used to model randomly changing systems that have the Markov property, where the future state is affected only by the current state, and not by states at previous time periods [15]. Obtaining a Markov model means getting two probability matrices: a transient probability matrix that expresses the probability of transitioning from one state to another according to the changes of the system, and an emission probability matrix that expresses the probability of an event being generated from a state. In the case in which the state of a system is fully observable and the system is controlled, Markov decision process can be applied, that is, a Markov model in which state transitions depend on the current state and an external action applied to the system.

A Markov model for estimating the mass in this study is designed as shown in Fig. 5. Each state is of the order of the DCT. The size of the transient probability matrix is $T \times T$, where T is the number of states. As there are no self-transition and backside transitions, $(t, t+1)$ elements of the transition probability matrix are 1, where $1 \leq t \leq T-1$ and others are 0.

The emission is related to the DCT coefficients. Distributions of the DCT coefficients at each state differ according to the impact mass. Fig. 6 compares the distribution of DCT coefficients according

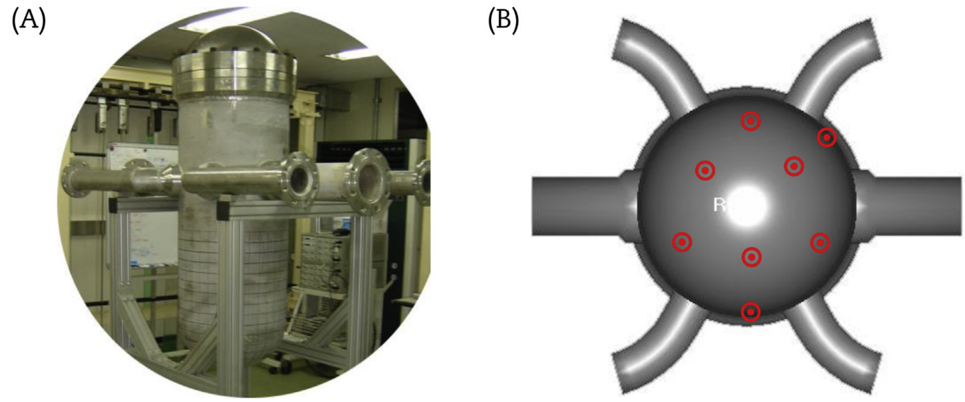

Fig. 3. Used mockup for obtaining impact signals. (A) 1/8-scaled mockup of a reactor vessel. (B) Positions of the attached accelerometers.

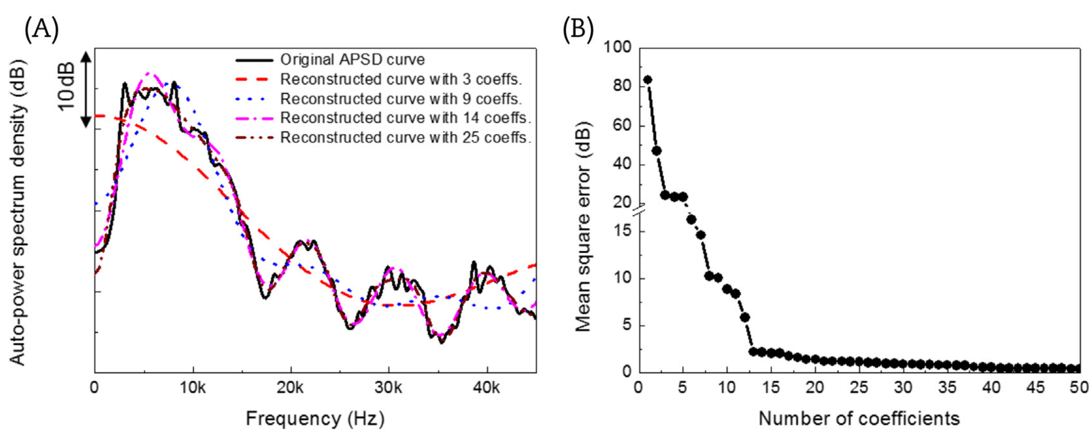

Fig. 4. Original APSD and reconstructed curves. (A) Comparison between the original APSD curve and a reconstructed curve with a finite number of DCT coefficients. (B) Mean square error between the original and reconstructed curves as a function of the number of DCT coefficients [11]. APSD, auto-power spectrum density; coeffs. = coefficients; DCT, discrete cosine transform.

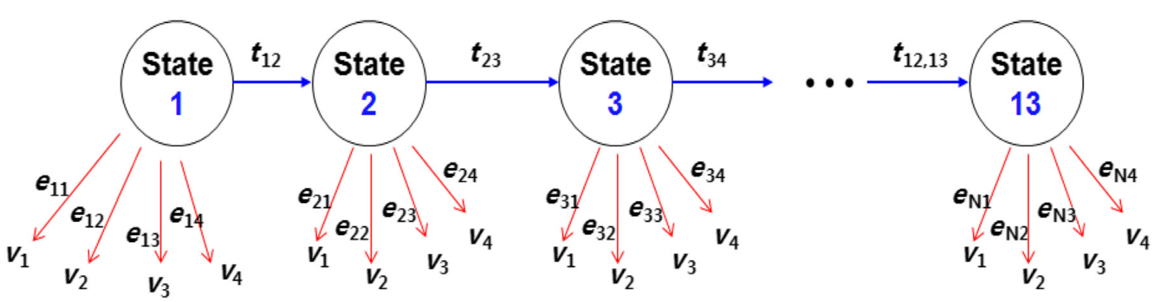

Fig. 5. Scheme of the Markov model used in this study.

to the mass. At low orders, the coefficients for which the mass is heavy are larger than those for which the mass is light. At higher orders, the investigation showed that the former are more widely distributed than the latter. This tendency exactly reflects the shapes of the APSD curves in Fig. 1 according to the impacting mass. In consideration of these kinds of differences, the codebook related to emissions is determined according to the impacting mass and installed accelerometer. At each order (i.e., each state), the distributed range of DCT coefficients is divided into a finite number of groups with the same interval, and the groups are allocated different letters (or colors).

Fig. 7 shows the whole process of making Markov models according to their mass and indicating the estimated mass. First, input sequences are obtained from the relationship between the codebook and DCT coefficients of the measured impact signals for a specific mass. Second, the Markov model is trained with sequences using the Baum–Welch iteration method [15]. Next, Markov models that correspond with other masses are obtained in the same manner; lastly, it indicates which arbitrary impact mass matches that among the trained impact masses, which was used. The test sequence related to the DCT coefficient from the impulse signal due to the arbitrary mass is applied to all Markov models, and the probabilities obtained from each Markov model are then compared with one another. Among them, the Markov model that has the maximum value is regarded as being related to the arbitrary mass.

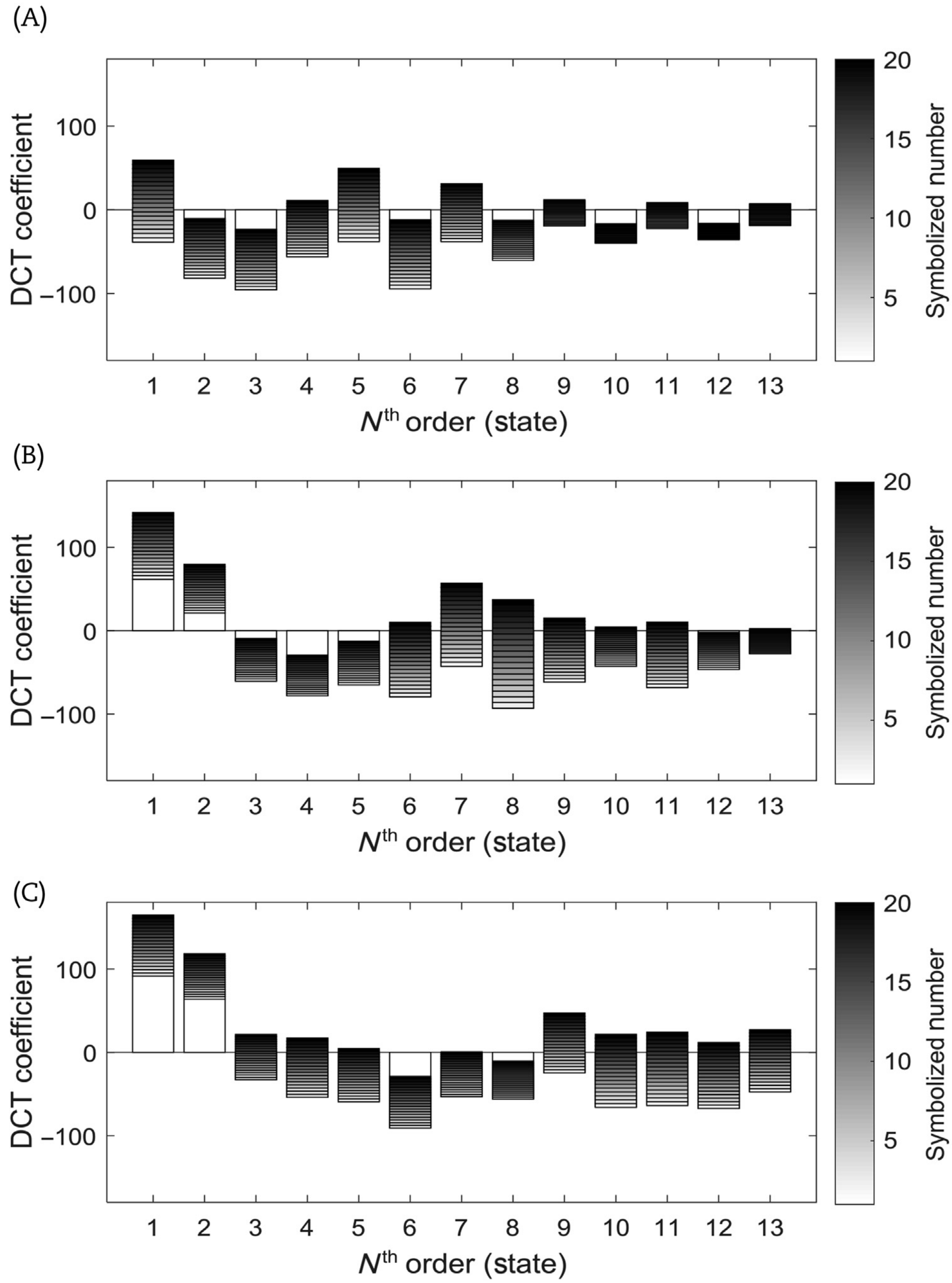

Fig. 6. Distributions of the DCT coefficient as a function of order according to mass. (A) 9.4 g. (B) 45.8 g. (C) 112 g. DCT, discrete cosine transform.

This study repeats the above process to get the optimal number of emissions for each state, and Fig. 8 shows the matching performance as a function of the number of emissions. Here, the matching performance is defined as the ratio of the number of cases that are identical to the real mass to the total training data. Thus, 20 emissions are chosen for the Markov model. In that case, the matching performance is above 85% for all masses and measuring positions, as shown in Fig. 9, and it shows that the Markov models in this study are well trained.

4. Comparison of mass estimation performance

Ninety-nine test data obtained from nine different masses were used to compare the mass estimation performance between the ANN model suggested in a previous study [11] and the Markov model designed in this study. The ANN model consists of input-signal hidden-output layers and uses 13 DCT coefficients, which is equal to the number of inputs used in the Markov model as input parameters. Fig. 10 shows the mass estimation performance of the ANN model. In the figure, "*relative error*" is defined as follows:

$$\text{Relative error}(\%) = \frac{1}{M}\sum_{i=1}^{M}\frac{|m_i - m_{real}|}{m_{real}} \times 100 \tag{4}$$

where M is the number of test data related to m_{real}, that is, the real mass of an impacting sphere, and m_i is the estimated mass. The averaged relative errors for all masses are below 35% except for two, 4.6 g and 9.4 g, relative errors of which are >120%. There are two

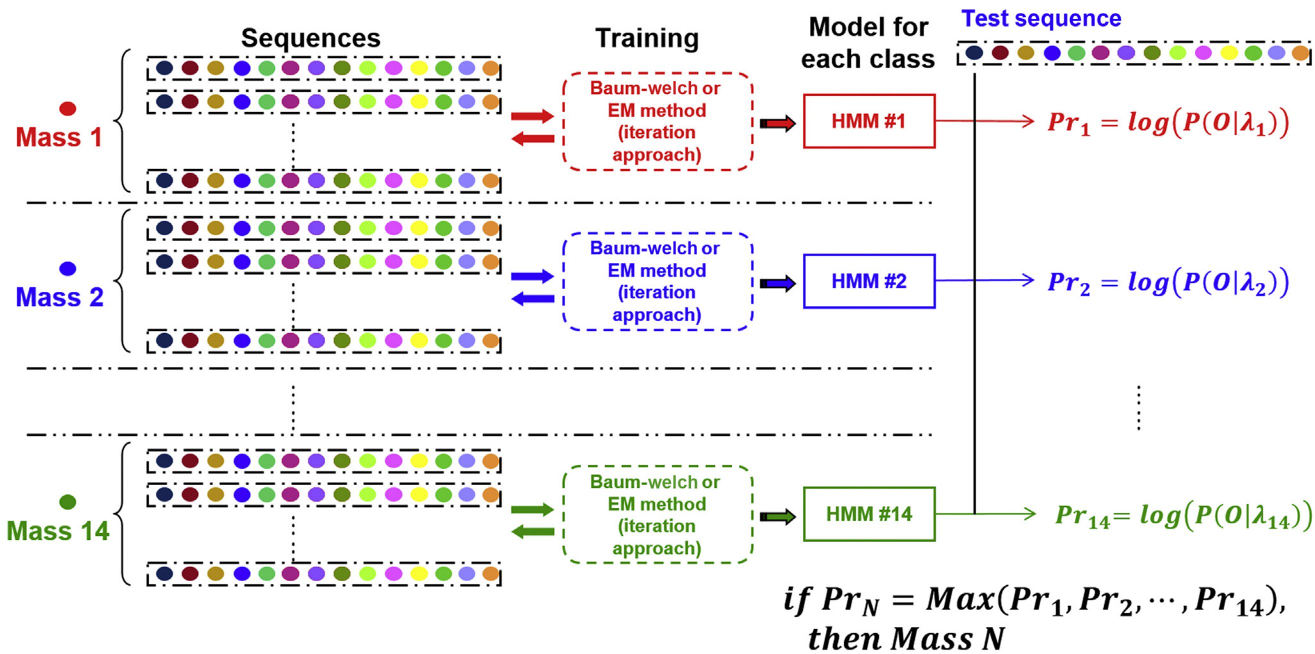

Fig. 7. Process of training the Markov model according to the mass and indicating estimated masses. EM, expectation-maximization.

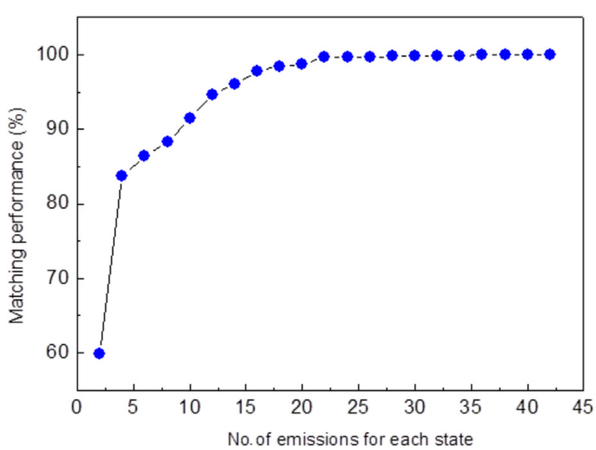

Fig. 8. Performance of the Markov model at estimating the mass as a function of the number of emissions in each state.

reasons for these large relative errors in the lighter masses: lighter masses could not sufficiently excite the large and heavy structure at the given velocity, and the resolution of the estimated mass by the ANN model could be larger than or similar to the light mass.

The same test data were applied to the proposed Markov models, and its estimation performance is represented in Fig. 11 as a "*matching error*" corresponding to the discrepancy between the real and estimated masses. The "*matching error*" is defined as follows:

$$\text{Matching error}(\%) = \frac{count(m_{real} \neq m_i)_{1 \leq i \leq M}}{M} \times 100, \quad (5)$$

where the function "*count*" is the total number of cases that satisfy the condition within the bracket. The matching errors of all masses are below 20% except the lightest mass, 4.6 g, which means that no more than two of the 10 cases are wrong estimation cases.

It is clear that both methods using ANN and Markov chain have improved the performance in terms of the size of estimation error compared with the conventional ones [16]. In the case of the ANN method, the absolute error bound is approximately 8–10 g, which shows that the estimation performance tends to improve as the mass increases. However, in the case of the Markov model, there is no distinct tendency between the mass and estimation performance, which shows that the estimation of the Markov model is dependent on the robustness of the training related to each mass. Although the Markov model has better performance than the ANN model for lighter masses, it is not easy to say which is clearly superior, because the errors caused by the two methods cannot be compared quantitatively.

As state above, the ANN model makes it possible to obtain the mass of impact object directly and it can then estimate the masses of arbitrary objects that are not used in its training. The Markov model judges whether an impact mass is coincident with one of the masses that were used in its training. Actually, the types of objects that can become loose parts in a reactor vessel or steam generator are various, such as strainer pieces and metallic fragments. Among them, there are limited accessories such as bolts and nuts that are likely to become loose parts through human error during regular overhaul. If the impact signals that employ accessories are used as the training data when making the Markov model, it may approximately identify both the type and the mass of the impact object simultaneously.

The result permits the conclusion that one can obtain a more robust estimated mass if the two methods using the ANN and Markov models are applied complementally. First, an impact mass is estimated by the ANN model. Next, the impact mass is compared with the mass estimated by the Markov model. If these estimations are similar, it becomes possible to guess the type of impact object. If not, the impacting object can be regarded as a new object that was not used in training either mass estimation model. This overcomes the drawback that the Markov model may only estimate the masses of loose parts used in its training. Finally, if one needs to add the new object into the category of recognizable objects, a Markov model can easily improve its performance by supplementing the codebook related to the object.

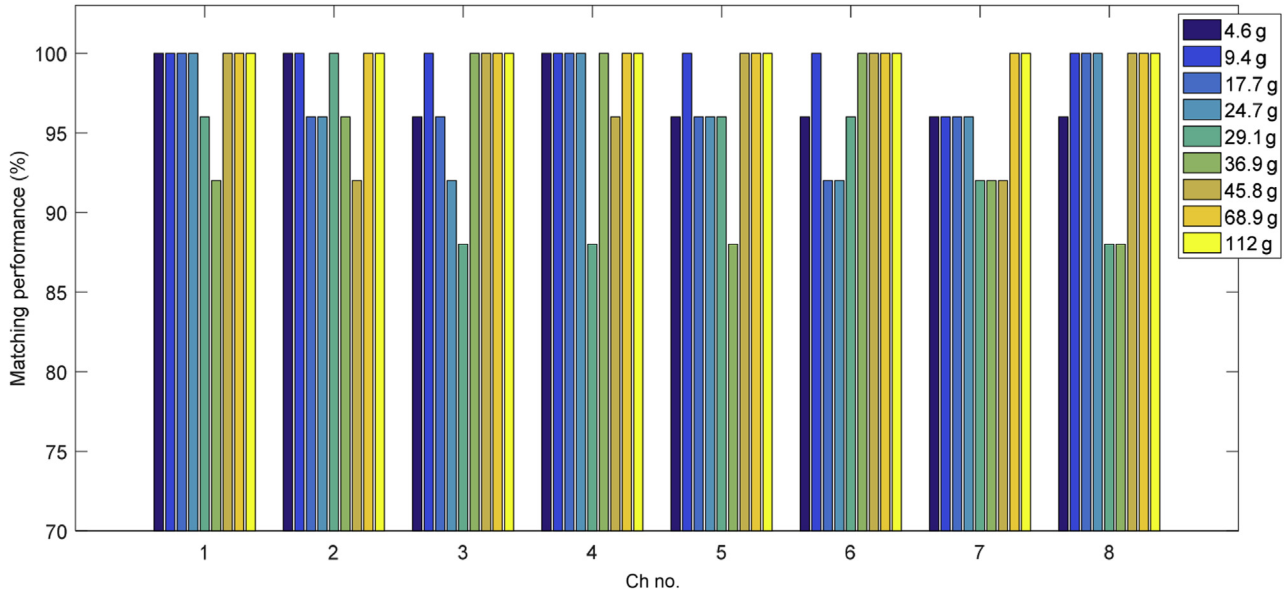

Fig. 9. Performance of the Markov model designed with 20 emissions at each state as a function of the trained masses and measured positions.

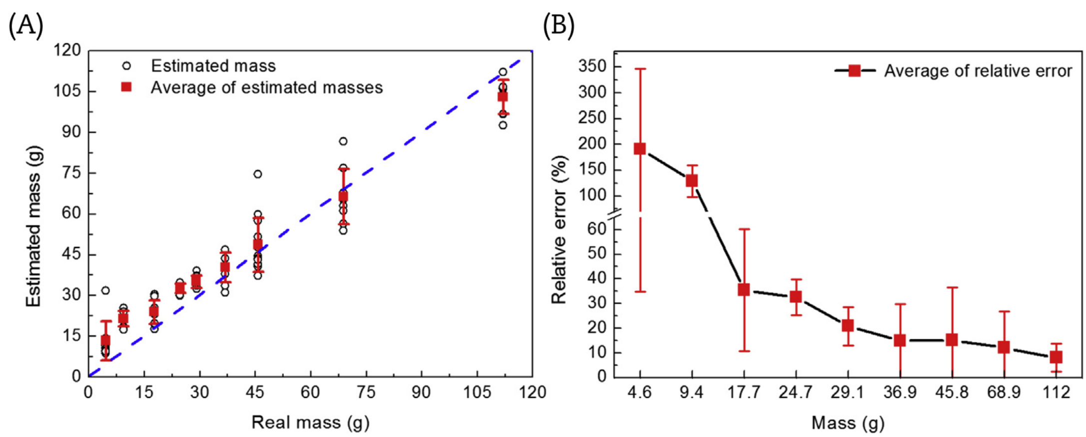

Fig. 10. Mass estimation performance by the ANN model as suggested in a previous study [11]. (A) Comparison between the real and estimated masses. (B) Relative error. The error bar is the standard deviation in each figure. ANN, artificial neural network.

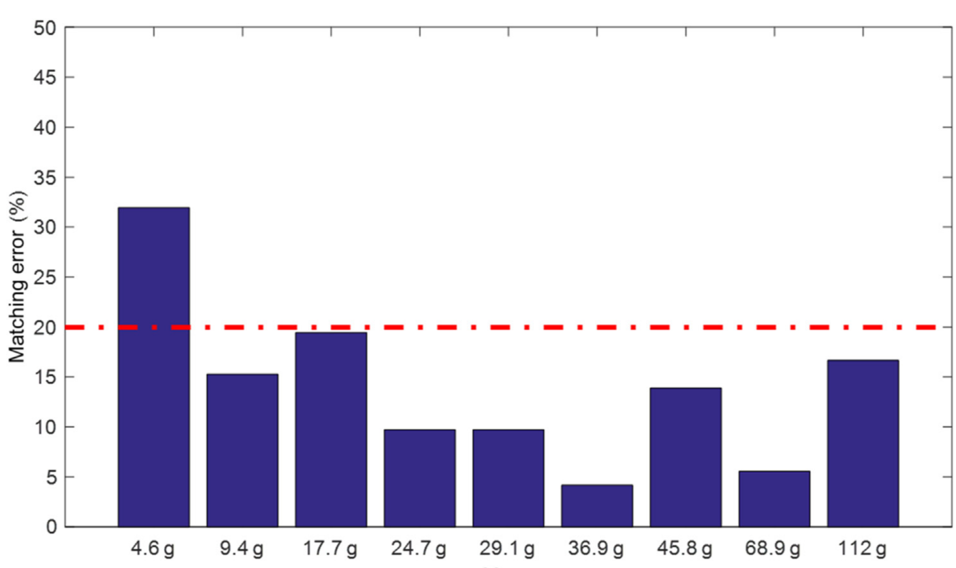

Fig. 11. Mass estimation performance of the designed Markov model.

5. Conclusion

This study proposed a method that uses a Markov model to estimate the mass of an impact object, and its estimation performance was compared with the results obtained via the ANN model in a previous study [11]. Both methods used the same feature vector consisting of 13 DCT coefficients related to the APSD of the impact signal as input variables. The ANN model could directly obtain the mass of the impact object through nonlinear regression analysis, and the *relative error* to the real mass was <30% for masses above 20 g. A Markov model could estimate the mass of an impact object and give information about its type by comparing it with previously trained masses. Its *matching error* representing the disagreement between the real and estimated masses was <20% except for 4.6 g objects. Since both errors had different meanings, it was difficult to say which method was more appropriate for estimating the impact mass. Nevertheless, investigation revealed that both methods had improved performance compared with conventional methods such as Hertz's impact theory and the FR method.

This study was conducted under two limited conditions; one was that all signals were obtained without internal flow and the other was that rigid spheres were used as impact objects. The former was not expected to affect the mass estimation performance because the frequency components due to internal flow were distributed within a low-frequency range below 1 kHz. However, further consideration would be needed in the case of the latter because the impact signals may vary depending on the shape of the contact surface during the impact.

Conflicts of interest

There is no conflict of interest.

Acknowledgments

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