Machine Learning Approach for Thinned Pipe Classification using Thickness Measurement Data of Nuclear Secondary Piping Systems

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1. Introduction

In order to prevent pipe burst events in secondary systems of nuclear power plants, continuous efforts for managing pipe wall thinning phenomena have been conducted. As a part of the pipe wall thinning management, hundreds of piping components are inspected during plant overhaul periods. The wall thickness inspections are conducted in a lot of points of mesh grids on piping components (e.g. elbow, tee, etc.), as shown in Fig.1.

Fig. 1. Pipe wall thinning management in secondary systems of nuclear power plants using UT thickness inspection for mesh grids on piping components.

Although reliable UT(ultrasonic test) methods were used for the thickness inspection, the measurement error is not ignorable compared with the wall thinning depth due to surface curvatures of piping components and field inspection environments[1,2]. Because of the thickness measurement error, the reliable value of thinning depth is very difficult to determine and even it is not clear whether the significant thinning is occurred in the inspected component or not. In this study, a simple machine learning approach for classification of thinned components and not-thinned components was tried.

2. Thinned Pipe Classification Algorithm

2.1 Previous Study using ANOVA Methods

EPRI(electric power research institute) had proposed several methodology to classify thinned and not-thinned piping component from their thickness measurement data[3]. Based on the EPRI's research, KEPCO E&C developed modified procedures, which were focused on the classification of locally thinned piping components using the ANOVA (analysis of variance) method[4]. A schematic explanation of the classification method is shown in Fig.2. The classification success probability of this method was shown to be better than that of the EPRI's method from probability experiments for hypothetical thickness measurement data.

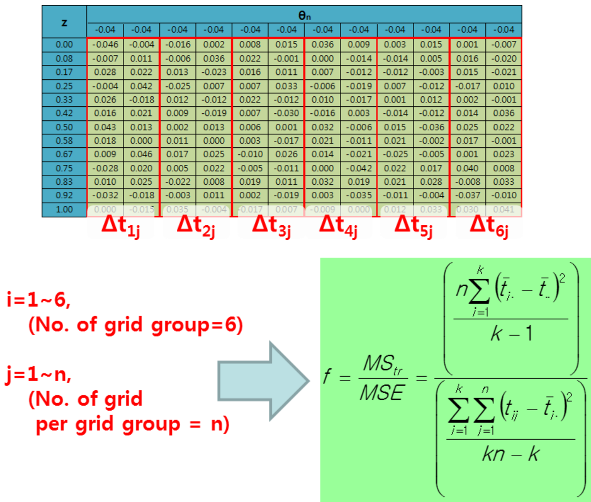


Fig. 2. Schematic diagram for the thinned pipe classification algorithm using ANOVA of the previous study [4].

3.2 Machine Learning Approaches

In this study, the SVM (support vector machine) classification algorithm (see Fig.3) was examined to learn supervised data for thinned and not-thinned piping components. In order to construct hypothetical thinning measurement data, the hypothetical thinning shapes were determined using random sampling for thinning parameter, then measurement simulations were conducted as shown in Fig.4. Total 20,000 data of (12$\times$13) grids for thinned and not-thinned situation, were used in this machine learning. Considering two points as follows, thinning depth ratio data for the nominal thickness, not the absolute value of thinning depth, were used in the machine learning.

- Thickness measurement error has the characteristics of a function of ratio for pipe wall thickness, which was presented in the previous study [2].
- For SVM application, the learning data have to be normalized. Data of thinning depth ratio is equivalent to normalization using pipe nominal thickness.

After data learning, the classification accuracy of the SVM classifier was checked using independently constructed test data. Fig. 4 shows the classification accuracy for several numbers of hypothetical measurement error (deviation ratio of test data = 0.2, 0.5, 1.0, 1.5 and 2.0, deviation ratio = thinning measurement deviation / thinning depth). As shown in Fig.4, the classification accuracy decreases with the increased measurement deviation.

In Fig.5, the accuracy of ANOVA classification algorithm was compared with SVM classifier results, in which the performance of SVM is significantly better than that of the ANOVA based classifier.

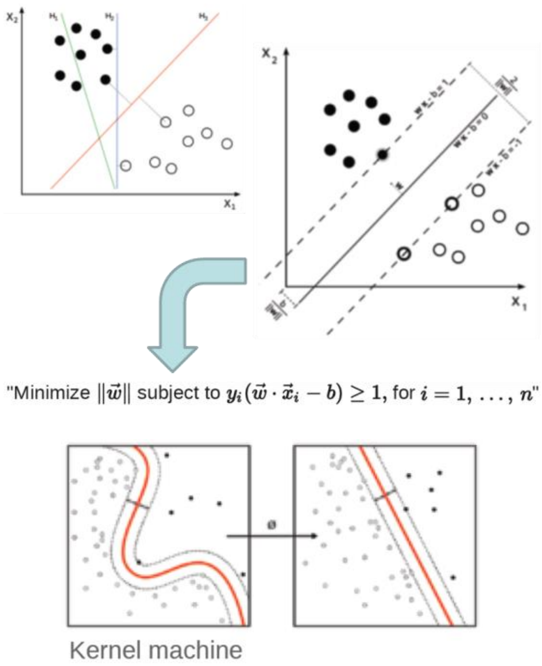


Fig. 3. Schematic diagram for support vector machine.

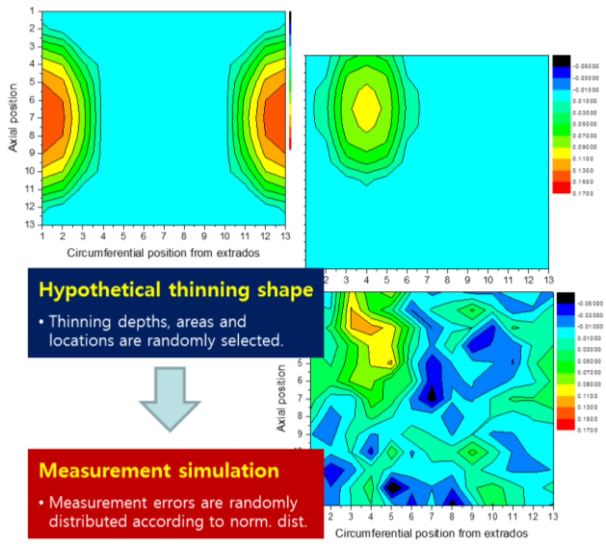
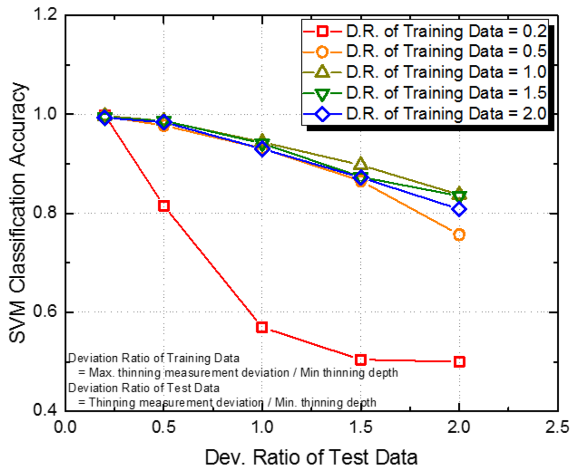
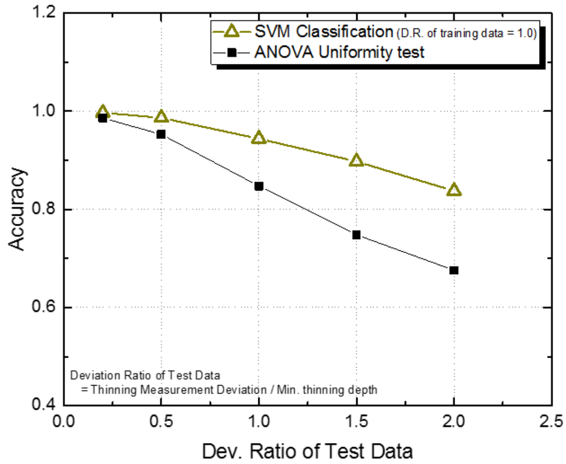


Fig. 4. Schematic diagram for hypothetical data construction.



(a) Dependency of SVM accuracy on hypothetical measurement deviation of training data



(b) Accuracy comparisons of SVM and ANOVA method

Fig. 5. Classification accuracies of SVM classifier and ANOVA method.

3. Conclusions

In this study, a machine learning classification algorithm was proposed for determining thinning states from the thickness measurement data of nuclear secondary piping systems. From the classification accuracy test for hypothetically constructed data set, the proposed algorithm is shown to be better than the ANOVA algorithm developed in the previous research.

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