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Anomaly Detection using Autoencoder based on Dimension Augmentation

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1. Introduction

Anomaly detection is a task that distinguishes between normal and abnormal states during data collection or continuous data acquisition [1]. It has been extensively covered in various fields such as nuclear reactor [2], sensing [3-5], and video surveillance [6, 7]. The advancement of deep learning technology is having an encouraging effect on the anomaly detection technology. Recently, deep anomaly detection has showed significant performance improvement in complex anomaly detection conditions [8]. Deep autoencoder-based anomaly detection system was applied to the high-flux advanced neutron application reactor (HANARO) at the Korea Atomic Energy Research Institute (KAERI) [2]. In deep anomaly detection, there is a certain range of change even in normal data; however, consideration of the uncertainty inherent in the data has not been actively utilized. We introduce a novel approach called dimensionality augmentation that can improve anomaly detection using deep neural networks. The idea is to improve anomaly detection performance by increasing the number of independent dimensions for anomaly scoring. This idea was applied to quantile autoencoder (QAE) [9] and QAE with abnormality accumulation (QAE-AA) [10], which improve anomaly detection performance by considering the aleatory uncertainty term. The proposed approach can contribute to the optimization of the anomaly detection system for HANARO.

2. Methods and Results

2.1 Anomaly Detection based on Autoencoder

Autoencoder (AE) is a kind of neural network used for data compression and data reconstruction. It consists of an encoder part and a decoder part as shown in Fig. 1. The encoder compresses the input into latent space, and the compressed data is decompressed and output the reconstructed data by the decoder. The difference between the input and output is called reconstruction error, which can be used to calculate scores for anomaly detection. Abnormal data is rare in most cases, so it is assumed that the most of training data are normal, hence the model learns the features of normal data. This type of learning is regarded unsupervised learning because the training data is assumed to be normal without using label information. After the model is fitted for the normal cases by minimizing the reconstruction error, the norm of the reconstruction errors of the normal data is smaller than that of anomaly. An anomaly can be detected by calculating an anomaly score based on the error and setting a threshold to classify whether an input is normal or not.

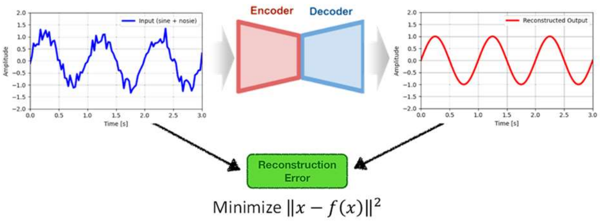

Fig. 1. Concept of anomaly detection based on autoencoder.

2.2 Dimension Augmentation for Anomaly Scoring

When using AE for anomaly detection, the anomaly score usually depends on the reconstruction errors. Accordingly, the data dimension for anomaly scoring corresponds to the input dimension, such as the number of sensors, signal channels, or table columns. We have shown theoretically and experimentally that increasing dimensionality of the data for scoring can contribute to anomaly detection performance improvement [9, 10]. The dimensionality increase can be achieved by adopting a data uncertainty term. The aleatoric uncertainty in the data is based on the channel-by-channel consistency of normal data, i.e., the range between lower and upper quantiles of the input. The uncertainty of anomalies can have different probability distribution from that in the normal data. Additional consideration of the channel-wise aleatoric uncertainty terms has the effect of dimensionality increase which contributes to providing additional scoring factors for anomaly scoring and then improving the anomaly detection performance. Moreover, the reconstructed output can be used for the model as a new input again, which produces the second reconstructed output, and this output also can be used to obtain the second reconstruction errors. When this process is repeated, more order reconstruction errors can be produced. QAE-AA [10] has shown that this repetition could enhance the anomaly detection performance.

2.3 Datasets

Datasets are used to determine the effectiveness of dimensionality augmentation for improving anomaly detection performance when using AE. The information of the datasets is described in Table I, referred to RaPP [11]. Unimodality (uni) means that there is one class that is a normal case. Multimodality (multi), on the other hand, means that multiple classes are normal cases. The total number of data is Nd. The dimensions of each input and each latent vector are Dx and Dz, respectively. Nc indicates the number of label classes.

Table I: Description of datasets [11]

Dataset	Modality	Nd	Dx	Dz	Nc	Anomaly Target
MI-V	Uni	23125	58	23	2	out of specification
MI-F	Uni	25286	58	23	2	not completed
RARM	Uni	20221	6	3	2	malfunctions
EOPT	Uni	90515	20	6	2	system failures
SNSR	Multi	58509	48	17	11	defective conditions

2.4 Experiments and Results

Datasets were split 6:2:2 (training:validation:testing) for the normal classes. The abnormal data is appended to be 50% proportion in the test set. AE, QAE, and QAE-AA were trained with the normal case only and tested for anomaly detection. The performance comparison was made based on the area under the receiver operating characteristic (AUROC) as shown in Fig. 2. A higher AUROC means easier and clearer anomaly detection. In the datasets except for EOPT, AE, QAE, and QAE-AA showed high anomaly detection performance in order, which indicates that increasing the dimensionality contributes to anomaly detection performance improvement. Because the dimension augmentation for anomaly scoring in both QAE and QAE-AA requires no additional data or training process, but rather makes full use of the aleatoric data attributes, so the proposed model has high practicality.

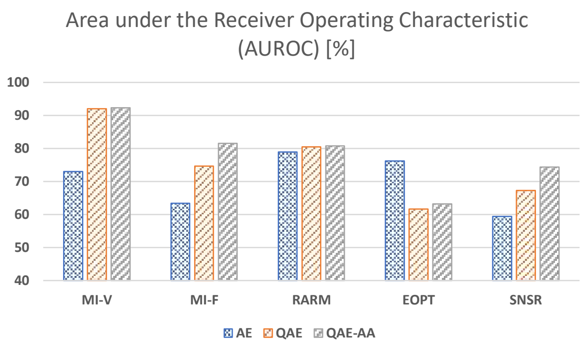

Fig. 2. Area under the receiver operating characteristic for datasets: MI-V, MI-F, RARM, EOPT, and SNSR.

3. Conclusions

Increasing the dimensionality for anomaly scoring is proposed to improve anomaly detection performance when using autoencoders. The concept is introduced in QAE and QAE-AA. QAE increases the dimension for scoring by additionally considering the range between lower and upper quantiles of the input data as an aleatoric data uncertainty term. QAE-AA iteratively uses the output of QAE again as input, thus generating more reconstruction errors and data uncertainty terms. Comparing the anomaly detection performance of AE, QAE, and QAE-AA revealed that the anomaly detection performance improved as the dimensionality increased. The proposed approach, dimension augmentation, is expected to improve anomaly detection performance by contributing to the optimization of the HANARO anomaly detection system.

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