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Application of Generative Model for Missing Signal Reconstruction in NPPs

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1. Introduction

It is obvious that proper decisions are essential for safer and more efficient operations of any industrial systems. Importance of making proper decisions is more emphasized if the system is safety-critical system such as nuclear power plant (NPP) or the system is under harsh conditions, since improper decisions may result in catastrophic loss of capital or high number of casualties.

Decisions in NPPs are mostly based on procedures and signals received from extensive amount of instrumentation systems. Therefore, faulty signals work as major impediments to making the proper decisions. According to the OPIS (Operational Performance Information System) provided by KINS (Korea Institute of Nuclear Safety), among total 738 nuclear incidents in Korea between 1978 and 2018, root causes of 215 (29.1%) incidents were instrumental problems [1]. Although not every instrumental problems are directly related to improper decision making, previous statistics support that the securing reliable instrumentation signals would significantly enhances the safety level of NPPs.

Accordingly, there have been many studies for enhancing reliabilities of instrumentation systems. Especially, with rapid advances on machine learning techniques, studies on detection and calibration of instrumentation errors, reconstruction of faulty signal from other signals, and prediction of unmeasured signal from other signals based on these techniques were actively conducted.

However, there is a lack of studies that dealing with multiple instrumentation system failure in NPPs [2, 3], although its significance was identified during Fukushima accident [4] and specified in NUREG-0800 [5]. Even more less studies were dealt with reconstruction of multiple missing signals under emergency situations, although multiple instrumentation system failure is much more likely to happen under harsh conditions. It may due to the difficulty of dealing with changeable correlations between signals corresponding to various plant conditions (e.g. accident type, location, severity, etc.) based on conventional approaches.

In this study, a signal reconstruction method which can reconstruct multiple missing signals regardless of prior knowledge on plant conditions was developed based on generative adversarial network (GAN), which has been widely applied to many fields while relatively unfamiliar in nuclear field.

In section 2, general concepts of GAN and proposed methods for signal reconstruction are briefly explained, and in section 3, related experiments and their results are described. Section 4 is concluding this paper with summary, current limitations, and future expectations on applications.

2. Methods

In this section, general concepts of GAN and proposed GAN-based signal reconstruction methods are briefly explained.

2.1 Background: Generative Adversarial Network

Generative adversarial network (GAN), which was recently introduced by I. Goodfellow et al. [6] is one of the generative models. GAN is a composite word of generative model, adversarial learning, and neural network.

GAN consists of two or more sub-networks that trained to achieve opposite goals. In most basic form of GAN (i.e. Vanilla-GAN), it includes two sub-networks, namely generator network and discriminator network (or simply generator and discriminator, respectively). Generator receives latent random vectors as inputs, and returns generated data as output, which has same form with real-world data. Discriminator receives both real-world data and generated data as inputs, and returns the values between 0 and 1, which implies the classification results of input data as real-world data or generated 'fake' data.

These two networks are trained toward opposite direction; generator is trained to generate more realistic data and to deceive discriminator, while discriminator is trained to correctly classify real data and generated data. After the proper training of GAN, generator becomes able to generate realistic samples (but not always same to real data) from given latent random vectors. In other word, generator is trained for proper mapping of latent random vector toward realistic data.

Unlike another widely applied generative model, variational auto-encoder (VAE) [7], GAN is implicit statistical model which does not requires pre-defined probability distribution model. This characteristic is regarded as double-edged sword, since it enables GAN to precisely mimic any kinds of data distributions theoretically while it also makes training process longer and to be more difficult. Representative challenges that emerge during training sequences of GAN can be summarized as follows.

- Premature convergence: GAN is not properly trained if generator or discriminator becomes far superior to the other.
- Loss oscillation: no matter how long GAN is trained, it may oscillates rather than converges.
- Mode collapsing: GAN may trained to model not the whole but only a portion of data.

GAN and other generative models are also suffered from a lack of quantitative performance metrics on 'level of reality of generated data'.

Although many studies have been conducted to cope with these challenges and corresponding fundamental solutions are not discovered yet, GAN still shows good performance in modeling complex data distributions in many applications. Especially, in image-related fields, GAN is widely applied due to its ability to generate clear and vivid images compare to other generative models.

2.2 Methods of GAN-based Signal Reconstruction

Fundamentally, proposed methods of signal reconstruction is similar to the process of reconstruction of damaged images [8]. However, since the characteristics of image data (static, high spatial correlations) are much different to that of instrumentation signal data (time-series, real-valued, low spatial correlations), its application strategies are different. Particularly, baseline GAN architecture, loss function, and performance metrics are major changes.

Development of signal reconstruction model consists of three steps. First step is pre-training step, which for making GAN model to generate realistic signal sets under various plant conditions. Second step is iteration step, which to find optimal latent vector for reconstruction of damaged signal set by minimizing pre-defined loss function. Final step is reconstruction step, which to reconstruct damaged signal set by replacing damaged parts of signal set with same parts of generated signals.

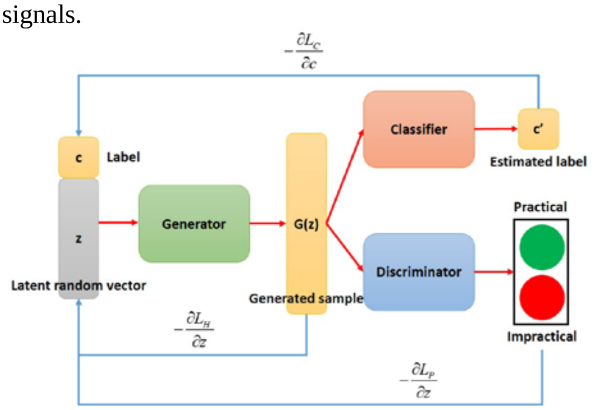

Fig. 1. Schematic of iterative process for finding optimal latent vector

Aforementioned pre-defined loss function for finding optimal latent vector consists of three kinds of loss elements. First loss element is homogeneity loss, which represents the level of difference between 'undamaged parts of damaged signal set' and 'corresponding parts of generated signal set'. Second loss element is classification loss, which represents the level of difference between classifier network's outputs (estimated labels) from damaged signal set and generated signal set. Third loss element is practicality loss, which represents how realistic the generated signal set is. Total loss is calculated by summing up these three loss elements with weighting factors λ_1 and λ_2, and optimal latent vector for reconstruction can be found by searching latent vector which minimizes total loss. Following equations are mathematical expressions of three kinds of loss elements and total loss.

$$L_H(z \mid i, M) = \| M \odot (G(z) - i) \|_1 \quad (1)$$

$$L_C(z \mid i) = \| C(G(z)) - C(i) \|_1 \quad (2)$$

$$L_P(z) = \log(1 - D(G(z))) \quad (3)$$

$$L_{total} = L_H(z \mid i, M) + \lambda_1 L_C(z \mid i) + \lambda_2 L_P(z) \quad (4)$$

Where $\boldsymbol{i}$ is input damaged signal set, $\boldsymbol{G}$ is generator network, $\boldsymbol{D}$ is discriminator network, $\odot$ is element-wise matrix multiplication operator, and $\boldsymbol{M}$ is the binary mask matrix which distinguishes damaged and undamaged parts of damaged signal set with binary values 0 and 1, respectively.

If found optimal latent vector for reconstruction is denoted as $\hat{z}$, corresponding reconstruction process can be mathematically expressed as follows.

$$\hat{z} = \arg\min_{z} \{L_{total}\} \quad (5)$$

$$\hat{x} = \| (M \odot i) + ((1 - M) \odot G(\hat{z})) \|_1 \quad (6)$$

Where $\hat{x}$ is reconstructed signal set.

3. Experiments

This section describes about experiments for validation of proposed signal reconstruction methods. Experiments were conducted in three stages; data acquisition and pre-processing stage, GAN model pre-training stage, and signal reconstruction stage.

3.1 Data Acquisition and Pre-processing

Since data on NPP emergency situation is extremely limited, experiments were conducted based on simulated data acquired from compact nuclear simulator (reference plant: Westinghouse 3-loop 900MW pressurized water reactor).

Four kinds of scenarios, including cold leg LOCA (loss of coolant accident), hot leg LOCA, SGTR (steam generator tube rupture), and MSLB (main steam line break) with varied break sizes (10~100cm^2 with 1cm^2 intervals, and for 10 times MSLB) were simulated. For instrumentation signals, following 31 kinds of signals that are important for making decisions were selected and obtained.

Table I: Obtained signals and from the simulation

Obtained signals	Units
CTMT sump level	m
CTMT radiation	mrem/hr
CTMT relative humidity	%
CTMT temp.	°C
CTMT pressure	kg/cm^2
Core outlet temp.	°C
Hot leg temp. (loop 1, 2, 3)	°C
Cold leg temp. (loop 1, 2, 3)	°C
Delta temp. (loop 1, 2, 3)	°C
PRT temp.	°C
H_2 concentration	%
RV water level	%
PRZ temp.	°C
PRZ level	%
PRZ pressure (wide)	kg/cm^2
S/G pressure (loop 1, 2, 3)	kg/cm^2
S/G narrow range level (loop 1, 2, 3)	%
Feedwater flow rate (loop 1, 2, 3)	ton/hr

For effective training of GAN model, following pre-processing sequences were applied.

- Simulated data was processed to have same time length (300 seconds of plant time).
- Simulated data was processed to have same time intervals (1 second) through interpolation.
- Unit data which has 30 seconds time length was generated.
- Measurement values were normalized to have values between -1 and 1.

3.2 GAN Model Pre-training

As baseline GAN architecture, RGAN (recurrent GAN) [9] which uses LSTM (long short-term memory) networks [10] was selected to effectively consider time-series data. Additionally, to consider the information on labels (accident type, location, severity, etc.) and to stabilize training sequences, concepts of InfoGAN [11] and MGGAN [12] were adopted. As a result, final GAN architecture includes five neural networks as its components, which are generator (G), discriminator (D), classifier (C), encoder (E), and encoder-discriminator (D_E).

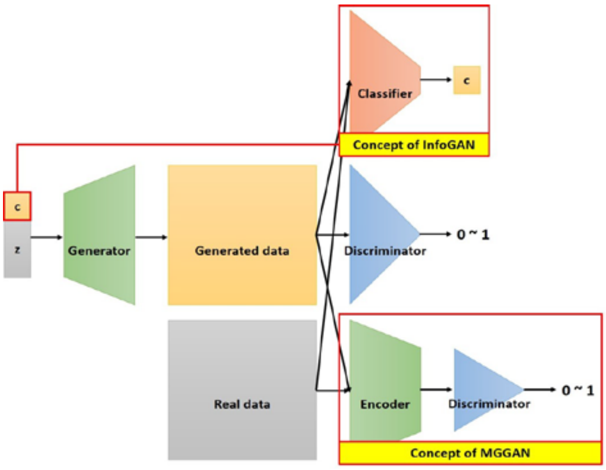

Fig. 2. Schematic of overall GAN model

Pre-training of GAN model starts from the training of guidance networks (encoder and encoder-discriminator), which were added from the concepts of MGGAN. Guidance networks are fixed after the sufficient training, and training of other parts of entire GAN model is initiated. As training data, about 50% of data was utilized.

To check whether the pre-trained GAN model is able to generate realistic signal sets or not, generative error performance metric was defined, which is a minimum deviation among deviations between generated signal set and entire simulated data. Also, to check whether mode collapse is occurred or not, indices of most similar training data were obtained.

Aforementioned pre-training sequences were repeatedly conducted with various hyper-parameter sets, by adjusting number of layers and nodes, LSTM sequence lengths, learning rates, latent vector size, and batch size. Adam optimizer [13] was used for optimization. GAN model which shown best performance among them was applied for signal reconstruction.

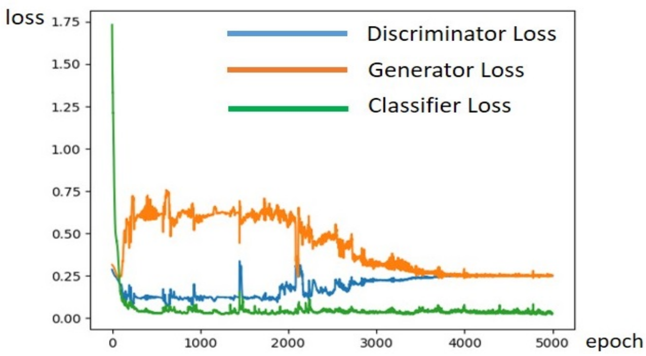

Fig. 3. Discriminator, generator, and classifier losses during training

3.3 Signal Reconstruction

To confirm that the pre-trained GAN model is able to reconstruct multiple missing signals, simulated data was intentionally damaged and proposed signal reconstruction methods were applied. In detail, among entire simulated data, randomly 1,000 data was selected and randomly selected kinds of signals were deleted.

Regarding iterative process for searching optimal latent vector for reconstruction, 750 iterations for each damaged signal set was applied. Among iterations, latent vector which shown minimum total loss was selected for further reconstruction process.

For the quantitative reconstruction performance estimation, mean reconstruction error, maximum reconstruction error, and standard deviation of reconstruction errors were considered.

As results, when 5 out of 31 signals were deleted, mean and maximum reconstruction errors were 4.51% and 21.71% respectively, and when 10 out of 31 signals were deleted, they were 5.37% and 34.67%. Detailed results are described in Table II.

Table II: Signal reconstruction performances according to the number of missing signals

# of missing signals (out of 31)	Mean Error (%)	Max. Error (%)	Error standard deviation
3	4.51	21.71	4.85
5	5.19	37.62	6.01
7	4.96	34.07	5.08
10	5.37	34.67	5.66
15	5.80	39.01	5.94

4. Conclusions

In this study, GAN-based signal reconstruction method for aiding proper decision-making under NPP emergency situations was proposed. For development, GAN architecture was established through merging concepts from RGAN, InfoGAN, and MGGAN. Also, loss function for iterative process and generative error performance metric for the evaluation of pre-trained GAN model were defined.

Through the experiments, it was shown that the proposed method is able to reconstruct multiple missing signals under emergency situations with acceptable error, without prior knowledge on plant condition.

Since the signal reconstruction performance is heavily depends on the quality of pre-trained GAN model, more precise optimization of underlying GAN model should be continuously conducted for further reduction of reconstruction error. Moreover, since proposed model can be applied only when the normal and faulty signals are accurately separated, study on detection of faulty signals under various emergency situations with acceptable error should be conducted.

It is expected that operators would become able to acquire sufficient amount of information for proper decision-making although there exists multiple missing signals, when fully developed system is applied. Developed system can be also applied with other support systems to enhance their performances and broaden their applicabilities, especially for support systems that heavily affected by input signals' reliabilities.

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