SEISMIC SIGNAL SYNTHESIS BY GENERATIVE ADVERSARIAL NETWORK WITH GATED CONVOLUTIONAL NEURAL NETWORK STRUCTURE

Yuanming Li[1], *Bonhwa Ku*[1], *Gwantae Kim*[1], *Jae-kwang Ahn*[2] *and Hanseok Ko*[1]

[1]School of Electrical Engineering, Korea University, Seoul, Rep. Korea
[2]Korea Meteorological Administration, Rep. Korea

IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium | 978-1-7281-6374-1/20/$31.00 ©2020 IEEE | DOI: 10.1109/IGARSS39084.2020.9323670

ABSTRACT

Detecting earthquake events from seismic time series signal is a challenging task. Recently, detection methods based on machine learning have been developed to improve the accuracy and efficiency. However, accuracy of those methods rely on sufficient amount of high-quality training data. In many situations, the high-quality data is difficulty to obtain. We address and resolve this issue by using a Generative Adversarial Network (GAN) model for seismic signal synthesis. GAN already shows its powerful capability in generating high quality synthetic samples in multiple domains. In this paper, we propose a GAN model with gated CNN which can excellently capture sequential structure of seismic time series. We demonstrate its effectiveness via earthquake classification performance. The results show the synthetic data generated by our model indeed can improve the classification performance over the one trained with only real samples.

***Index Terms*—** deep learning, data augmentation, earthquake detection, generative adversarial network

1. INTRODUCTION

For decades, realizing accurate earthquake detection has been a critical task. Detecting earthquake events with different durations via same detection algorithm still remains as a challenging task for the researchers who work on developing automated earthquake detection methods [1,2]. In recent development of artificial intelligence, however, various deep learning techniques have been applied to many time series detection tasks [3]. Thibaut Perol et al. [4] proposed a deep learning algorithm composed of convolutional neural networks (CNNs) and showed that it is more computationally efficient with better accuracy performance, compared to some prominent traditional machine learning algorithms. Moreover, there have been several studies on earthquake detection through various deep learning algorithms [5, 6]. With such research efforts, recent advances in deep learning has shown to play a critical role in modern seismology.

A well-known problem with deep learning, however, is that it needs to train with sufficient data. Having a large dataset is crucial for producing reliable performance of the deployed deep learning model. This problem can be addressed and resolved by various data augmentation techniques. In particular, it is possible to increase the algorithms performance of existing data through deep learning based data augmentation. In traditional method of data augmentation in machine learning, it would be just simple scaling, shifting and flipping of the training data. However, these methods cannot lead to a robust improvement of performance because the diversity of the data available for training is not fully achieved.

Generative adversarial network (GAN) is a type of generative models applied to data augmentation. It is designed based on an adversarial min-max game between two networks, generator and discriminator. The main idea is to sample from a simple distribution like Gaussian and learn to map this noise to data distribution using neural networks. This is achieved by an adversarial training of these two networks. Researchers have successfully applied it to image synthesis, audio waveform generation, and speech synthesis [7–9]. In most recent studies, due to its excellent performance, GANs have begun to be used in seismology [10]. Tiantong Wang et al. [11] proposed a GAN that can produce high quality seismic waveform samples with either earthquake events and non-earthquake events. However, there is still a significant gap between real events and synthetic events. In addition, the authors did not show frequency information of the results.

In this paper, we propose a GAN with gated CNN structure that can produce realistic synthetic earthquake signals. In the generator model design, to better learn the characteristic of seismic samples, we apply a gated CNN to capture the sequential and hierarchical structures of earthquake signals [12]. For discriminator model, we employ ConvQuakeNet which is an excellent earthquake classifier [4]. To generate diversity synthitic data, we utilize an instance normalization layer in the generator model. We then evaluate the quality of synthetic earthquake events in two methods: (1) visualization and (2) quantitative evaluation. The results of this study indicate that the proposed GAN model is a promising method to augment seismic event dataset.

2. DATA PROCESSING

Our earthquake dataset is provided from KMA (Korea Meteorological Administration). The seismic dataset is from January 2016 to July 2018. In the dataset, the magnitude of earthquake events is greater than Mw 3.0. We use continuous ground velocity records from 256 local stations and record the seismic signal at sample rate of 100Hz on 3-channe. The total number of earthquake events is 6,145.

Our classification contains 2 classes in machine learning terminology: class 0 corresponds to noise without any earthquake, and class 1 correspond to earthquake events. We extract two types of 10-s-long windows from these streams: windows containing events and windows free of events (noise), so that the size of each sample is (1000, 3). The starting point of event windows is p-arrival time. The samples are visually presented in Fig. 1. For classification test, the non-earthquake events are randomly sampled when the earthquake does not occur. The ratio of earthquake events and noise events is 1:1.

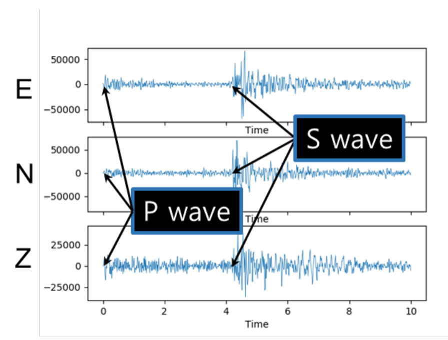

Fig. 1. Sample of earthquake event.

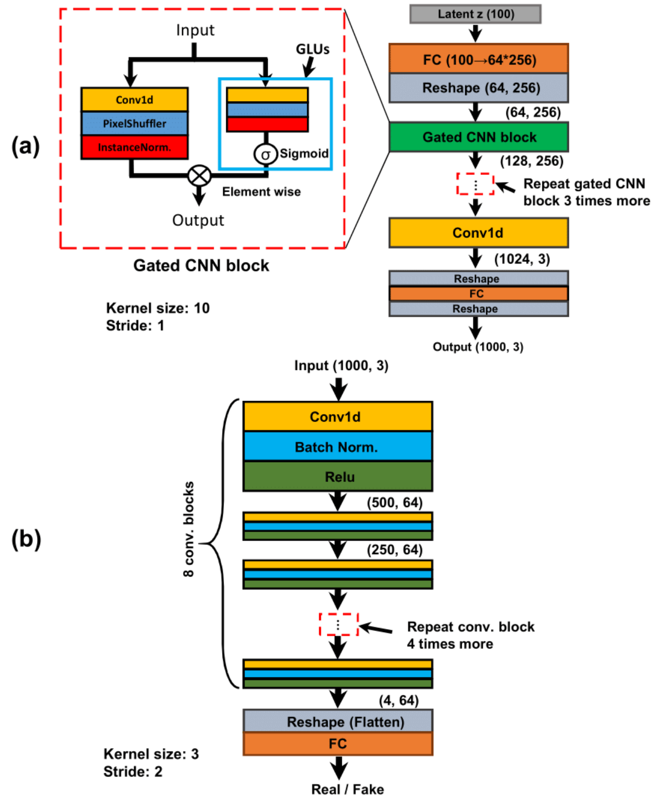

Fig. 2. Architecture of our model. (a) and (b) are architectures of generator and discriminator, respectively.

3. PROPOSED METHOD

Our model is built on the structure of GAN which is composed of generator model and discriminator model. The generator model generates synthetic data instances, while discriminator model identifies them for authenticity.

3.1. Generator architecture

As mentioned above, an earthquake simulation GAN model previously proposed by Wang et al. is called 'EarthquakeGen' [15]. The generator of their proposed model is composed of three pipelines to generate each channel of the data individually. This structure was shown to generate realistic earthquake signals. In contrast, our generator can generate realistic earthquake signals adequately without requiring the three pipelines structure.

The generator learns real seismic samples containing 3 channels of 1D time series length of 1, 000. We use one-dimensional (1D) CNN structure as our generator. The 1D CNN can help capture the overall relationship along with the feature direction without changing the temporal structure. In order to capture the sequential and hierarchical structure better, a gated CNN is used wherein gated linear units (GLUs) are used as activation function

The output of the gated CNN block is selectively propagated by GLUs. The structure of gated CNN block is shown in Fig. 2(a). It is composed of a CNN block and a GLU. The GLU is just to add a sigmoid function after another CNN block and $\otimes$ is element-wise product between matrices. Furthermore, instead of transposed CNN, we use pixel shuffler convolutional layer for upsampling [13]. This is effective for solving the problem of checkerboard artifact. After that, the instance normalization layer is employed, which can improve the results of generator [14]. The main framework of the generator is composed of several gated CNN block, as shown in Fig. 2(a). In addition to this, to adjust the channel dimension and output size, we apply 1×1 convolution and then finally a fully connected layer.

3.2. Discriminator architecture

The discriminator model is similar to the earthquake events classifier [5]. It is already confirmed as an excellent seismic feature extractor. Moreover, the less computation of model can significant reduce the runtime of our model. As shown in Fig. 2(b), our discriminator is composed of eight 1D convolutional layers and a fully connected layer. Instead of pooling layer, the stride of convolution is 2. After convolutional layer, we use a batch normalization to increase the performance of the model. The activation function employed is nonlinear rectified linear unit (ReLU), which is taken after each batch normalization layer.

4. EXPERIMENTS

4.1. Training details

It is noted that while there is a large enough amount of non-earthquake events to train the model, annotated data are scarce and usually hard to obtain. Thus, in the GAN training, we just use the earthquake events dataset. To focus more on the feature of earthquake events, as mentioned above, we crop the data starting at p-arrival time with 10-s-long window. For the loss function, we compare three kind of loss functions; original loss function, least square loss function, and Wasserstein loss function. In the results, the model trained with original loss function is shown to produce the best performance.

For optimization, we use the ADAM algorithm, and the learning rate is set to 10^{-4}. In the GAN model training process, the batch size and epoch is set to 64 and 1000, respectively.

4.2. Evaluation via visualization

In these experiments, we assess two models, baseline and our proposed model. The baseline model is based on DCGAN. The baseline is modified to a form which is more suitable for earthquake events generation. Based on these models, some synthetic earthquake event samples and real earthquake event samples are shown in Fig. 3. In order to analyze the experiment results overall, we compare both time series and spectrogram of the synthetic data. Obviously, baseline and our model can generate the synthetic samples similar to the real data shown in Fig. 3(e) visually. Nevertheless, the important issue of the baseline is that most of the synthetic samples is similar to each other. In other words, the synthetic samples generated by baseline are not diverse. It is attributed to the model that cannot learn the comprehensive distribution of real data. In the results of our model shown in Fig. 3, the synthetic samples share similar characteristics to the real samples. The more important point is that our model maintains the diversity of the synthetic samples. However, through the comparison of the spectrogram, there is still a gap in the characteristics of frequency information. In the spectrogram of real data, the distribution of frequency range is almost less than 40 Hz. The frequency ranges of some synthetic samples exceed this value.

4.3. Evaluation via classification

In another evaluation method, we assess the quality of synthetic samples by the 'ConvQuakeNet' model [5]. To simulate an environment where number of training data is less, we select 800 samples from real dataset as a training data. Besides, the 800 synthetic samples are added to the real data to

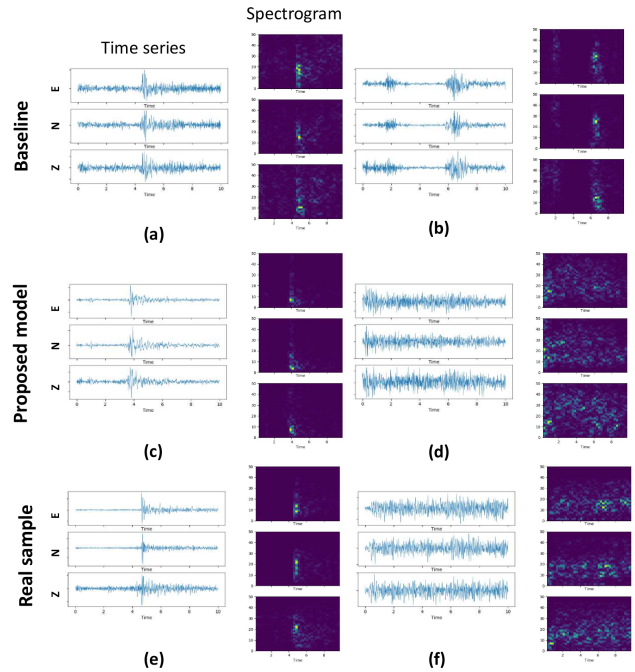

Fig. 3. Samples of synthetic earthquake events (a) - (d) and real earthquake events (e)(f).

set up the augmentation datasets. We use the learning rate of 10^{-4} for training the classification model. The batch size and training epoch are 128 and 200, respectively. In addition to this, for the non-earthquake events as shown in Table 1, we use 3 datasets to train the classification model. The augmentation A and B are augmented with synthetic data from baseline model and our model, individually. The result shows that the classification accuracy and true positives which trained with 'augmentation B' are the highest than the others.

Table 1. The classification results of the classification model trained with real data, augmentation A and augmentation B. The Augmentation A and B are datasets augmented by baseline model and our model, respectively.

Datasets	Accuracy	True positives	True negatives
Real data	90.56	82.84	98.28
Augmentation A	93.50	91.67	95.34
Augmentation B	97.30	97.06	97.55

We further examined on the quality of our model with different size of data augmentation. We still used 800 real samples, and added the different size of synthetic data. The number of augmentation size is as follows: 0, 200, 400, 800, 1200, 1600 and 2000. Here, "0" means only real samples exist. We can observe the results in Table 2, the results indicate the synthetic samples can significant increase the performance of classification model. It validates that our model can

Table 2. The classification results of data augmentation with different synthetic data size generated by our model.

	0	400	800	1200	1600	2000
Accuracy	90.56	92.89	97.30	95.59	92.77	92.03
True positives	82.84	92.40	97.06	94.36	92.89	90.20
True negatives	98.28	93.38	97.55	96.81	92.65	93.87

generate realistic data. The accuracy is decreased with the synthetic data size over the 800. This is due to the augmented dataset containing some low-quality synthetic data. Through these experiments, we conclude that the synthetic data generated by our GAN model can increase the performance of classification.

5. CONCLUSIONS

We proposed a GAN model for seismic signal synthesis with a gated CNN structure embedded in generator module. Compared to the baseline model developed by DCGAN, the synthesis results in time series plot and spectrogram showed that our proposed model indeed can learn the characteristics of earthquake better than simple data augmentation schemes or DCNN based baseline. In addition, the synthetic samples were shown to exhibit characteristics of more diversity. Furthermore, the classification results were shown to prove that accuracy is increased significantly with the data augmentation by our model.

6. ACKNOWLEDGEMENT

This work was supported by Meteorological/Earthquake See-At Technology Development Research Grant (KMI2018-09610). (Corresponding author: Hanseok Ko)

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