Applicability of Data Augmentation Through Variational Autoencoder for Two-Dimensional Acoustic Emission Source Discrimination on Hollow Cylindrical Structures

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ABSTRACT

A data augmentation method is studied in this work to supplement previously proposed variational autoencoder (VAE) based acoustic emission (AE) source discrimination tool. The VAE model distinguishes the sources of collected AE signals through the multiple Lamb mode arrivals resulting from helical paths. It displayed the ability to discriminate pencil-lead-break (PLB) waveform dataset collected at a liquid nitrogen tank by source locations. VAE infers source-discriminative latent variable distribution conditioned on the observed waveforms and can be further applied to localization predictions for unseen waveforms. However, the prediction will be limited to source coordinates included in the training dataset. Therefore, this work studies the applicability of data augmentation using VAE to approximate waveform envelopes from sources coordinates that are not included in the PLB dataset, which are called target source in this study. Approximated waveforms of target source were introduced by interpolating the learned mode arrival characteristics to augment the original dataset. The augmented data set trained an updated latent variable distribution that accounted for the target source. Actual waveforms from target source were projected to updated latent space and validated the effectiveness of augment waveforms. This positive outcome provides confidence on pursuing data augmentation applications through VAE to assist AE localization.

Keywords: acoustic emission, variational autoencoder, data augmentation

INTRODUCTION

Acoustic emission (AE) is a class of elastic wave that can be excited by transient release of stress due to structural defects. It has become a common passive monitoring target for many structural materials, including steel, concrete, and composite plates [1,2,3,4]. AE studies often surround making inferences on the collected data for defect localization [4] or classification [5]. Moreover, the recent hype in data-driven approaches, specifically deep learning applications [6,7], drives up the demand on acquiring larger dataset to ensure results. Common practices for simulating AE events are pencil lead break [10] (PLB) or impact testing that can take a significant amount of time to construct a desired dataset. Therefore, data augmentation methods are proposed to help create such dataset. Ai et al. [8] used numerical results from finite element model with added gaussian noises as an augmented dataset to replace AE data acquisition. It was applied in a single receiver zonal source localization exercise on a 0.30m by 0.61m stainless-steel plate. Guo et al. [9] conducted source localization with deep learning framework that the training dataset was augmented by deactivating channels of the recorded AE events, which have 8 channels for each incident. The above two works enlarged the size of dataset by adding flavors into the original data and improved the model performance.

For metallic hollow cylindrical structures, the authors have proposed a source discrimination variational autoencoder (VAE) tool in previous work [11]. It used the multiple mode arrivals caused by helical paths and Lamb modes as characteristics to differentiate waveforms by the source coordinates. The two-dimensional source coordinates are reflected by the first two orders of helical paths and the path lengths can be observed by the delay of arrival between the Lamb modes. The VAE model captures these characteristics and was able to separate waveforms into source-discriminative latent variable distribution. Such latent variable distribution provides latent representation of the sources included in the training data, which will be called training sources, that can be used toward source localization when an unseen waveform is projected into the latent space. However, the prediction will be limited to training sources. Therefore, a data augmentation approach is proposed to approximate the not-included source coordinates, called target sources, to expand the resolution on source localization. First, a latent representation of target source will be approximated by interpolating, proportional to the helical path length, from the learned mode arrival characteristics. Then, the generative decoder of VAE samples around the approximated latent representation and simulates waveforms from target sources. The generated waveforms supplement the collected dataset to account for the target source. The performance of the proposed data augmentation will be validated by mapping the actual waveform from target source onto the latent variable distribution trained on augmented dataset. Noted that this work will focus on the direct distance between AE source and receiver rather than the 2D source coordinate as a feasibility study of the proposed approach.

The article is structured as follows: The methodology section introduces the mode arrival characteristics, VAE source discrimination and proposed data augmentation method. The result section reviews the performance of the proposed method. The conclusion section discusses the applicability of data augmentation made by VAE and future works.

METHODOLOGY

Previous work [11] has presented that the lengths of the first two orders of helical path is a mapping for two-dimensional (2D) source coordinates. The lengths of helical paths are retrieved from waveforms by the delays between two Lamb mode arrivals: fundamental symmetric (S0) and anti-symmetric (A0) modes. The first order helical path length can be observed by the delay between first S0 mode and first A0 mode; the second order helical path length reflects in the delay between first and second S0 mode arrivals. A variational autoencoder was implemented to capture the described mode arrival characteristics and provided source-discriminative latent variable distribution to differentiate the source coordinates of the collected waveforms. VAE captures the mode arrivals by fitting mixture normal distribution density function to the waveform envelopes. The collected dataset was labeled by the source coordinates that the latent representation of the coordinates included in the training dataset can be derived from taking the expectation over latent variable distribution of waveforms from the same source. This article narrows down the source discrimination object into only the direct distance between source and receiver as an initial studying on applicability of data augmentation done by VAE. Therefore, the data augmentation method exercise of this article focuses on the time delay between first S0 and A0 modes, which is the characteristic that distinguishes the direct distance.

Figure 1 presents the simplified VAE source-discrimination workflow on the direct distance, which is the 1st helical path. This modeling method can make predictions by projecting unseen waveforms onto a trained latent space that the prediction will be made by the closest latent representation. However, it will heavily rely on the training dataset to construct dense enough latent representation grids for prediction resolution. A data augmentation approach is proposed to supply waveform envelopes of sources not included in the training dataset.

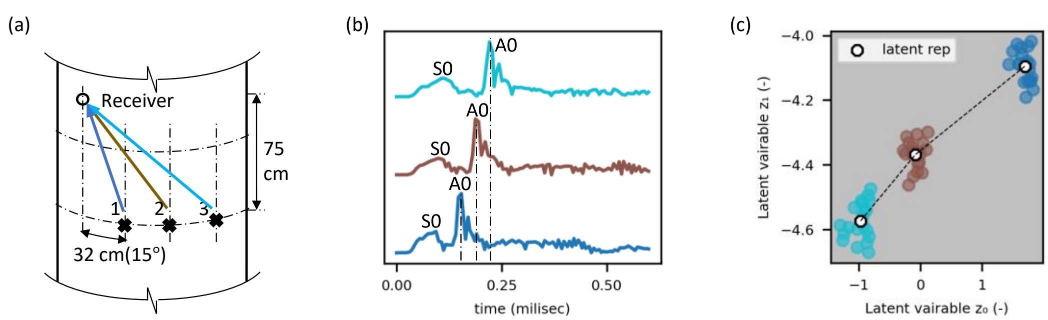

Figure 1. Simplified source-discriminative VAE workflow (a) sources of collected waveforms at a 2.42m liquid nitrogenous tank, (b) mode arrivals reflecting the change in direct distance and (c) the source-discriminative latent variable space.

The proposed data augmentation leverages the source-discriminative latent variable space of the VAE model to produce approximated waveform envelopes of target source, which is the source not included in the training dataset. In a trained VAE model, a set of mode arrival characteristics is learned from the sources included in the training dataset, which are named training sources in this study, motivate the source-discriminative latent space, and can be modeled by normal distribution:

$$(\mu_i, \sigma_i^2, \emptyset_i)^{train_j} \sim N\left(\boldsymbol{\mu}_{\boldsymbol{i}}^{train_j}, \boldsymbol{\sigma}_{\boldsymbol{i}}^{\boldsymbol{2}\,train_j}\right) \tag{1}$$

where $(\mu_i, \sigma_i^2, \emptyset_i)$ are the mixture normal distribution parameters describing mode arrival characteristics and $\left(\boldsymbol{\mu}^{train_j}, \boldsymbol{\sigma}^{\boldsymbol{2}\,train_j}\right)$ are the mean and variance of learned parameters on the jth training source. For this direct distance problem, $\boldsymbol{\mu}^{train_j}$ of training locations are proportional to the 1st helical path and $\boldsymbol{\sigma}^{\boldsymbol{2}\,train_j}$ captures the uncertainties embedded within the data acquisition process. Therefore, parameters for waveform envelopes from target source are inferred from these learned characteristics. Specifically, it is sampled from a normal distribution with mean interpolated by the ratio of 1st path lengths and averaged variance of the two training sources:

$$\varphi = 1 + \left| \frac{h_1^{train_j} - h_1^{target}}{h_1^{train_j} - h_1^{train_{j+1}}} \right| \tag{2}$$

$$(\mu_i, \sigma_i^2, \emptyset_i)^{target} \sim N(\varphi * \boldsymbol{\mu}^{train_j}, \frac{\boldsymbol{\sigma}^{2^{train_j}} + \boldsymbol{\sigma}^{2^{train_{j+1}}}}{2}) \tag{3}$$

where h_1 is the 1st helical path length, φ is the h_1 ratio between training and target sources. This augmentation process estimates the time delay between S0 and A0 mode arrivals for target source with the uncertainties observed in the collected waveforms. With the inferred mixture normal parameters, waveform envelopes to augment training dataset are provided by plugging the parameters into the density function:

$$\hat{\boldsymbol{x}} = mixture((\mu_i, \sigma_i^2, \emptyset_i)^{target}) \tag{4}$$

$$\hat{\mathcal{D}} = (\boldsymbol{x}, \hat{\boldsymbol{x}}) \tag{5}$$

which $\boldsymbol{x}, \hat{\boldsymbol{x}}$ indicate the waveform envelopes from training dataset and interpolated parameters; $\hat{\mathcal{D}}$ is the augmented dataset. An augmented latent variable distribution for $\hat{\mathcal{D}}$ is trained to provide an updated latent variable distribution that takes target source into account. The performance will be reviewed by prediction accuracy of updated latent space on actual waveforms from the target source. For this applicability study, three sources from the PLB dataset collected at the 2.42-meter diameter liquid nitrogen tank are used which the locations are already shown in Figure 1.a. Location 1 and 3 are the training sources and location 2 is the target source. Each location has 20 waveforms that the ones from training sources will be used in training and the waveforms recorded at target source are used for reviewing prediction accuracy of the augmented latent space.

RESULTS

Figure 2.a displays the latent space of VAE model conditioned on training sources. The model was able to separate the waveform envelopes from the two training sources. Figure 2.b shows the distribution of mode arrival characteristic, learned by VAE, of the mixture normal component that describes the arrival time of A0 mode. It conforms to the observed A0 mode delay shown in Figure 1.b. The distribution of arrival characteristic used for approximating waveform from target source is shown in red at Figure 2.b. The parameter was sampled by normal distribution center on the mean interpolated by 1st helical path length with averaged variance of learned characteristics. Approximated waveforms for target source were generated by the sampled parameters and were mapped back into the latent space of training sources in Figure 2.a. The approximated waveforms showed a similar distribution as Figure 1.c, which was trained on the full three sources. The model generated waveforms were then augmented into the original training dataset.

Figure 3 shows the latent variable distribution of augmented dataset. The augmented latent space presented source-discrimination regardless the waveform envelopes are collected in experiment or model generated. Moreover, actual waveform envelopes from target source were projected onto augmented latent space after training. It can be observed that model generated waveforms have good mixing with actual waveforms from target source that supports the effectiveness of proposed data augmentation approach. Taking the closest latent representation as a predictor, the presented augmented latent space has 90% accuracy on correctly identifying the target source when actual waveforms were sent into the model. The two wrong predictions are the ones closer to location 1 cluster. As a result, the proposed data augmentation demonstrated its ability on approximating waveforms from sources not included in the training dataset under this simplified localization study.

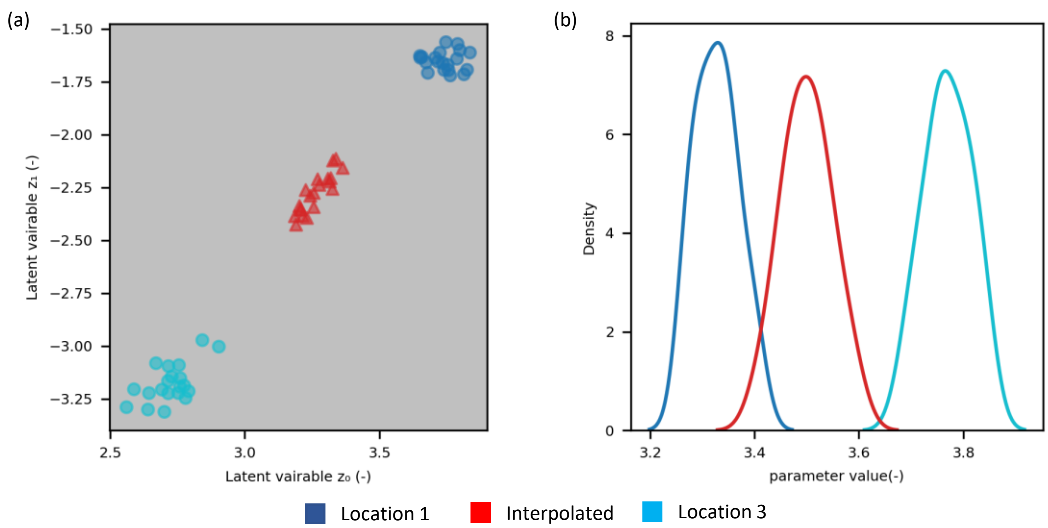

Figure 2. Data augmentation process (a) latent space of training sources and (b) learned mode arrival characteristic

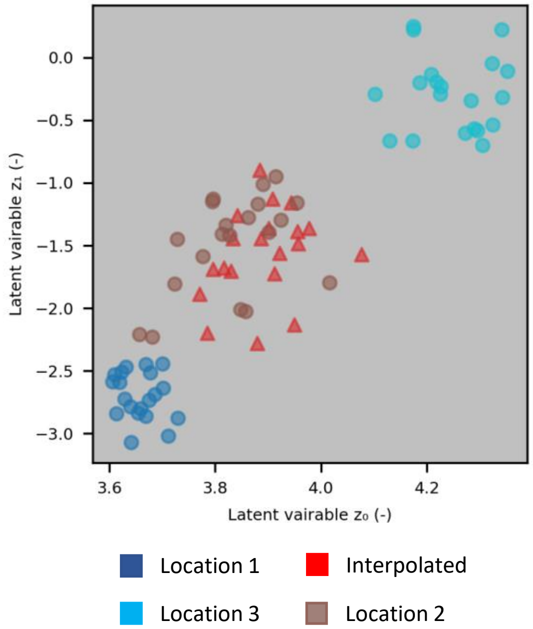

Figure 3. Augmented latent space with actual waveforms from target source overlayed for performance review

CONCLUSION

A data augmentation approach is proposed to provide finer resolution on localization prediction of previously presented waveform-based localization VAE model. The augmented dataset accounts for AE waveforms from source coordinates that are not collected in experiments. A simplified modeling that focused on the direct distance between source and receiver were implemented to study the applicability of proposed data augmentation method. The result suggested that the augmented dataset assisted the model to identify a waveform from a source not included in the training dataset. Future work on this method includes expanding the approach to 2nd helical path that completes the full 2D source-discrimination. Also, it will include more training sources and generalize the approach to the entire surface of hollow cylindrical structure. Lastly, even though this augmentation method is manipulating the mode arrival time resulting from change in path lengths, it can be also be tweaked into compensating the velocity shifts. For example, this augmentation approach has potential to help training dataset adopting velocity changes under different temperature conditions.

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