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Ultrasonic Guided Wave Dispersion Compensation Based on Fourier Basis Convolutional Autoencoder

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Abstract: Ultrasonic guided waves are widely used signals in industry, but their inherent dispersion and multimodal characteristics significantly impact practical applications. Considering the frequency-dependent nature of guided wave signals, this paper proposes a Fourier-based convolutional autoencoder (FCAE) algorithm for dispersion compensation in ultrasonic guided wave signals, thoroughly investigating its practical application in handling ultrasonic guided wave signals. The neural network model combines the time-frequency analysis characteristics of Fourier bases and the nonlinear mapping capability of neural networks to learn the time of flight (TOF) of guided wave modes. Through this approach, the model successfully eliminates phase distortion and energy leakage caused by Lamb wave dispersion in guided wave signals, thereby significantly improving the quality and interpretability of the signals. The proposed Fourier-based neural network model's effectiveness in dispersion compensation is validated through simulation experiments, providing robust support for further applications of ultrasonic guided wave technology.

Key Words: Fourier Basis, Convolutional Autoencoder, Ultrasonic Guided Wave, Dispersion Compensation

1 Introduction

Ultrasonic guided waves are a technique that utilizes the propagation of ultrasonic waves in solids for detection and analysis. This technology introduces ultrasonic waves into materials and monitors the changes in the propagation path, velocity, and amplitude of the waves to obtain information about the internal structure and condition of the material. Ultrasonic guided waves are commonly used in areas such as non-destructive testing, structural health monitoring, and material property assessment. In practical applications, ultrasonic guided waves are often employed in monitoring and detecting flat structures, including single-layer plates and composite plate structures composed of multiple layers. Lamb waves and horizontal shear waves are two modes of ultrasonic waves that can propagate in flat structures. Lamb waves, in particular, are widely applied due to their flexible excitation and detection methods and strong interaction with plate defects.

However, Lamb waves exhibit dispersion and multimodal characteristics, which make them complex and intriguing in engineering applications. The dispersion relation of Lamb waves describes the relationship between the frequency of the wave and the wave number or group velocity, indicating that different frequency components propagate at different speeds in the plate. The dispersion relation for Lamb waves is complex and is typically solved using numerical methods. Factors such as the geometric shape of the structure, material elastic constants, density, etc., influence the dispersion relation of Lamb waves. Different Lamb wave modes correspond to different dispersion relations, and due to the presence of thin plates or film structures, multiple wave modes can exist for Lamb waves. The number of specific modes depends on the geometric shape and material properties of the structure. Common Lamb wave modes include A0 mode, S0 mode, A1 mode, etc., each corresponding to different wave propagation paths and vibration forms. In practical applications, different Lamb wave modes may couple, leading to the transfer and conversion of wave energy as it propagates through the structure.

In ultrasonic testing and structural health monitoring, studying the dispersion and multimodal characteristics of Lamb waves helps determine the appropriate detection frequency and mode to accurately identify and assess defects and damage in the structure. Dispersion compensation of guided wave signals can enhance the resolution of Lamb wave signals, greatly expanding the monitoring and detection capabilities of ultrasonic guided waves in industrial applications. Traditional algorithms often focus on dispersion compensation for a single mode. Wilcox [1] proposed a rapid signal processing technique called Time-Distance Mapping (TDM), which maps the signal from the time domain to the distance domain, compressing dispersed signals back to their original shape. Xu et al. [2] introduced the Time-Distance Mapping method into phased array imaging, improving the inspection accuracy of phased arrays. Liu [3] introduced a wave number-based linear mapping technique, using Taylor linear approximation to truncate the Taylor expansion to nonlinear terms, transforming the nonlinear dispersion relation into a linear relation. Introducing compressive sensing theory into dispersion compensation is beneficial for compensating

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multimodal signals. Nokhbatolfoghaha [4] proposed an adaptive dictionary learning framework that updates the dictionary matrix to better adapt to complex structures. Recently, deep learning has also been introduced into dispersion compensation. Wang et al. [5] investigated Lamb wave imaging using compressive sensing and deep learning. Zhang [6] proposed a new method based on a convolutional autoencoder for Lamb wave dispersion compensation. The convolutional autoencoder is employed to learn the relationship between the signal and the TOF. Subsequently, based on the excitation signal and TOF, the signal is compensated.

This paper proposes a dispersion compensation method that combines Fourier bases with neural networks. Fourier bases aid neural networks in extracting frequency information, facilitating the learning of TOF, and subsequently compensating the signal for dispersion.

2 Dispersion Compensation Methods

For a single-mode propagation distance x, the morphology of the ultrasonic guided wave after propagating to a specific distance can be obtained in one dimension:

$$u(x,t)=\frac{1}{2\pi}\int_{-\infty}^{\infty}F(\omega)e^{j\omega t}e^{-jkx}\mathrm{d}\omega \tag{1}$$

The term k represents the dispersion relationship. For waves propagating in the forward direction, ω and k have the same sign. The Taylor expansion is applied to k:

$$k=k(\omega)=k_0+k_1(\omega-\omega_0)+k_2(\omega-\omega_0)^2+\cdots \tag{2}$$

Where, ω_0 is the center frequency of the excitation signal, k_0 is the wave number at the center frequency. The coefficients k_1 and k_2 are the Taylor expansion coefficients. Due to the nonlinearity in the wave number k, a first-order approximation is made for the wave number:

$$k(\omega)=k_0+k_1(\omega-\omega_0) \tag{3}$$

At this point, the relationship between wave number and frequency is linear. The dispersion of the signal only manifests as a phase shift, without affecting the propagation time and signal width. This is also the fundamental principle of dispersion compensation. The signal propagated over a specific distance is given by:

$$y_0(t)=u(x,t)|_{x=x_0}=\frac{1}{2\pi}\int_{-\infty}^{\infty}F(\omega)e^{j(\omega t-kx_0)}\mathrm{d}\omega \tag{4}$$

Based on the Fourier transform, it can be expressed as:

$$Y_0(\omega)=F(\omega)H(\omega) \tag{5}$$

Where $H(\omega)=e^{-jkx_0}$, $Y_0(\omega)$ is the Fourier transform of the signal $y_0(t)$. Since $h(x)$ does not introduce dispersion:

$$\begin{aligned}h(x)&=\frac{1}{2\pi}\int_{-\infty}^{\infty}H(k)e^{ikx}\mathrm{d}k\\&=\frac{1}{2\pi}\int_{-\infty}^{\infty}e^{-jkx_0}e^{jkx}\mathrm{d}k=\delta(x-x_0)\end{aligned} \tag{6}$$

$H(k)$ is interpolated by $H(\omega)$ using Equation (3), the non-dispersive signal propagated to a distance x can be expressed as:

$$\begin{aligned}y_{i\_c}(t)&=\frac{1}{2\pi}\int_{-\infty}^{\infty}F(\omega)e^{j(\omega t-k^{'}x_i)}\mathrm{d}\omega\\&=f(t-t_i)=f(t)*\delta(t-t_i)\end{aligned} \tag{7}$$

From the above equation, it can be seen that the non-dispersive signal is only related to the TOF. Once the TOF is known, the non-dispersive signal can be directly obtained. To obtain the TOF, this paper employs a model that integrates the Fourier basis with the Convolutional Autoencoder (CAE) model to accurately extract TOF. The main body of this model still adopts the encoder-decoder architecture, as shown in Figure 1, where y represents the input data, and y' represents the output.

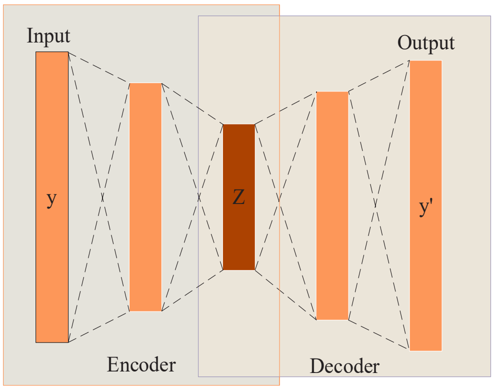


Fig. 1: The Convolutional Autoencoder

Traditional autoencoders are widely used in feature learning, denoising, and other fields. The input signal undergoes multiple convolution operations to learn its main features, and then the deconvolution operation is the reverse process, i.e., reconstructing the signal from features. In general, people aim for high similarity between input and output signals. However, in this paper, we aim to learn the Time of Flight (TOF) of the signal, which can be used for dispersion compensation operations.

To extract frequency information, the first layer is set as a custom layer to implement the Fourier transform of the input data. In fact, since the Fourier basis of the first layer is usually set to be smaller than the length of the input data, this transformation can be considered a short-time Fourier transform, which can balance both frequency and time information.

To enhance efficiency, convolution and transpose convolution operations are introduced in the encoder-decoder architecture, forming a Convolutional Neural Network (CNN) structure to reduce the number of weights and connections.

In the convolutional autoencoder used in this paper, each convolutional layer is followed by a batch normalization layer and an activation layer, enabling both feature extraction and efficient model training. At this stage, for a learned feature h_i, it can be represented as:

$$h_i=f_{ReLU}(f_{BN}(W_i*y+b_i)) \tag{8}$$

Where, W_i represents the weight of the convolutional layer, b is the bias, $f_{BN}(\bullet)$ is the batch normalization layer, and the activation function layer is chosen to use $f_{ReLU}(\bullet)$. This approach combines the advantages of autoencoder learning complex mappings and the efficient feature extraction of convolutional neural networks, providing an effective means for dispersion compensation. The transformation from features to the final output can be represented as:

$$y_{\mathrm{ToF}} = f_{\mathrm{ReLU}}\left(f_{\mathrm{BN}}\left(\tilde{W}_i * h_i + c_i\right)\right) \tag{9}$$

The weight of the deconvolution layer is denoted by $\tilde{W}_i$, c_i is the bias term, and the chosen optimization function is mean squared error (MSE). According to Equation 6, the labels of the output signal can be expressed as:

$$y_{TOF}^{\mathrm{label}} = \sum\nolimits_j A_j \delta(t - t_j) \tag{10}$$

Where A_j is represents the amplitude of each wave packet. Therefore, the parameters are optimized by minimizing the error between the decoded output and the given label:

$$L_{\mathrm{MSE}} = \left(y_{\mathrm{ToF}} - y_{\mathrm{ToF}}^{\mathrm{label}}\right)^2 \tag{11}$$

Where, y_{ToF} is the decoded output.

The experimental design is illustrated in Figure 2. A set of cosine and sine waves with frequencies equal to the excitation signal's center frequency, each lasting for one period, are taken. These cosine and sine waves are sliced and rearranged based on the convolution kernel size to form the first convolutional layer. After data reading, convolution is performed between the data and the cosine and sine waves. Subsequently, the square, sum, and square root operations are applied to the cosine and sine at corresponding positions to achieve Fourier convolution. The subsequent network layers follow the standard convolutional autoencoder structure, incorporating batch normalization and activation operations between each convolutional or transposed convolutional layer.

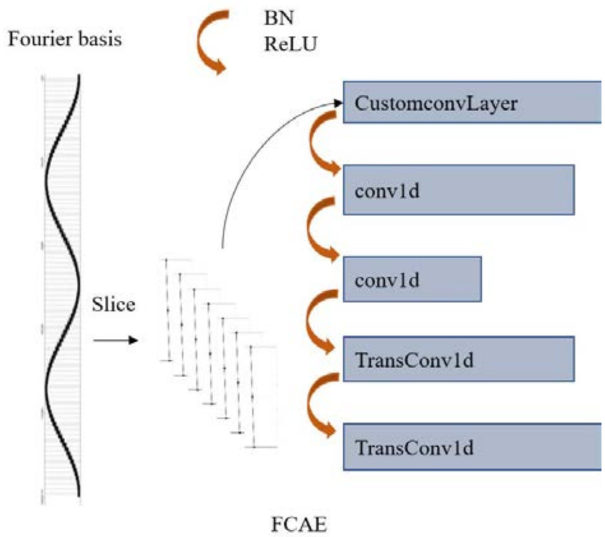


Fig. 2: Fourier Basis Convolutional Autoencoder

3 Simulation Verification

3.1 Data simulation

In order to validate the effectiveness of the proposed method, this section introduces its application in numerical simulation experiments.

The open-source software Dispersion Calculator [7] is utilized to calculate the dispersion curves required for generating signals. A 1mm thick aluminum alloy plate is selected as the material, and its parameters are shown in table 1, including the dispersion information for the A0 and S0 modes, such as $k(\omega)$, $c_g(\omega)$, and $c_p(\omega)$. Subsequently, a 5-cycle hanning window modulated signal with a center frequency of 100 kHz is chosen as the excitation. The propagation distance ranges from 0 to 1m, divided into 5000 points. The sampling frequency is set at 10MHz, and the sampling time extends to 1ms. All amplitude values are set to 1. The excitation signal is shown in Figure 3.

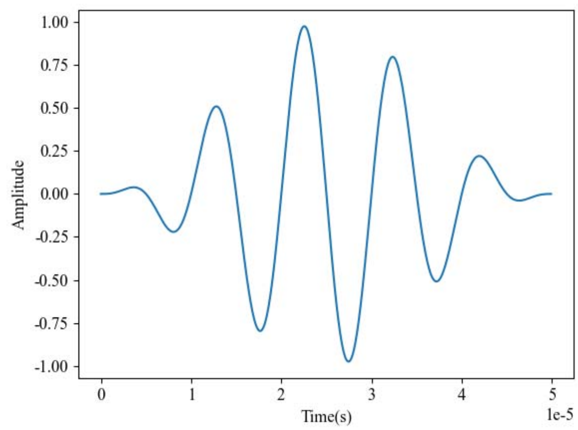


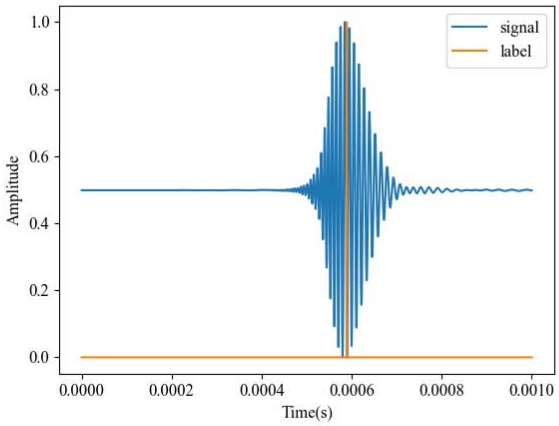
Fig. 3: The excited signal

For the case of a single wave packet, 5000 sets of data are generated for both A0 and S0 modes, combined to form 10,000 sets of data. For two wave packets, the signals of both modes are superimposed, with one mode having a randomly chosen propagation distance. For three wave packets, an additional set of randomly chosen propagation distance and mode is added to the two-wave packet scenario. In each case, The dataset is divided into a training set with 9000 data samples and a test set with 1000 data samples.

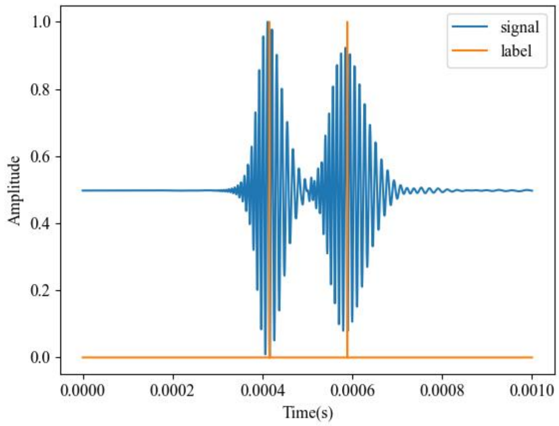
Table 1: Aluminum alloy material parameters

Density(kg/m^3)	2710
Young's Modulus(Gpa)	69
Poisson's Ratio	0.33
Thickness(mm)	1

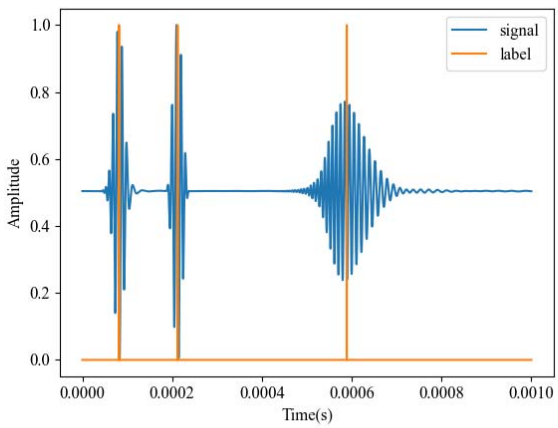
The generated signals are normalized, as shown in Figure 4. The dispersion phenomenon becomes more pronounced as the excitation signal propagates a certain distance. This dispersion leads to a spreading of the Lamb wave packet in the time domain, resulting in a temporal elongation of the waveform. The consequence of this dispersion is a reduction in the resolution of the signal, making it challenging to discern specific features, especially when multiple wave packets overlap. In such cases, the individual components of the signal become intricately intertwined, posing difficulties in isolating and distinguishing their respective characteristics. This temporal spreading, or dispersion, is a critical consideration in Lamb wave signal processing and underscores the need for effective compensation techniques to restore signal clarity and facilitate accurate analysis.



(a) Single wave packet



(b) Double wave packet



(c) Triple wave packet

Fig. 4: Different wave packet data

3.2 Numerical results

The encoding part of the FCAE model includes a custom layer and four convolutional modules. Each convolutional module comprises one convolutional layer, one batch normalization layer, and one ReLU activation layer. The custom layer is directly connected to the next convolutional module after passing through the batch normalization layer. The decoding part comprises four deconvolutional modules, with each deconvolutional module consisting of one deconvolutional layer, one batch normalization layer, and one ReLU activation layer. It's worth noting that the last deconvolutional module does not have a batch normalization layer, and the activation function chosen is sigmoid.

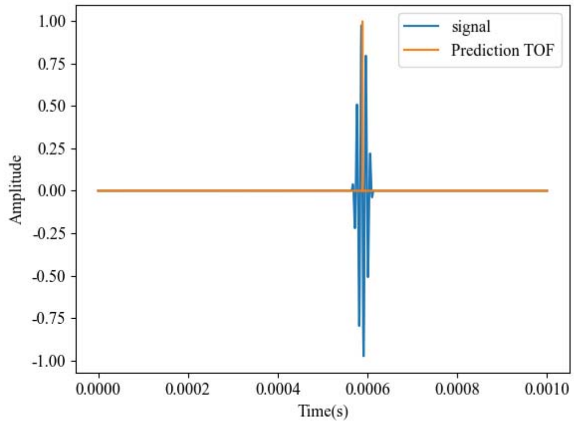
The Fourier-based convolutional layer utilizes single-cycle sine and cosine waves with a frequency of 100 kHz, which are rearranged to form a convolutional layer with a kernel length of 3. The layer undergoes operations such as element-wise multiplication, squaring, summing, and square root to achieve Fourier transformation. The kernel sizes for the other convolutional layers are 3, 3, 3, 3, and for the deconvolutional layers, they are 5, 3, 3, 2. Except for the custom layer and the final deconvolutional layer, the stride for all other convolutional and deconvolutional layers is set to 2. The number of kernels for these layers is set to 33,4,8, 16, 32, and 32, 16, 8, 1. The accuracy is calculated by considering the coordinates of the maximum values in the output results compared to the labels. Since each sample contains 10,000 data points, when calculating accuracy, we consider points within a range of 10 points around the true label as accurate. In this case, the error is less than 1e-6 seconds, which can be neglected. However, if the number of data points in the sample is small, such errors should not be ignored.

The framework is implemented using PyTorch, with a batch size of 128. The model is trained using the Adam optimizer. The learning rates for single and double wave packet modes are both set to 1×10^{-4}, L2 regularization is applied with a coefficient of 1×10^{-5}, and for the triple wave packet mode, the learning rate is set to 5×10^{-6} with a regularization coefficient of 5×10^{-5}. The Mean Squared Error (MSE) is used to calculate the loss.

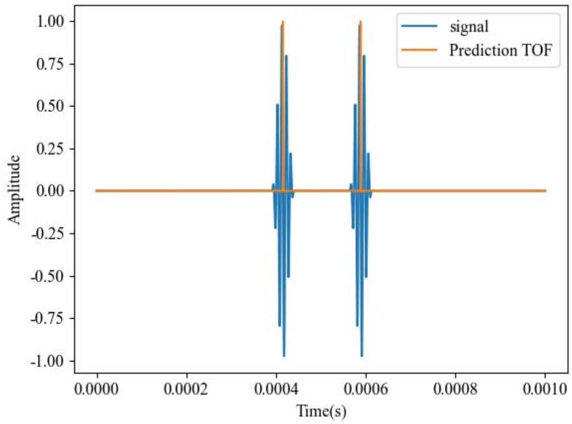
Table 2: Testing result

case	Accuracy	
	CAE	FCAE
Single wave packet	85%	85%
Double wave packet	77%	81%
Triple wave packet	75%	80%

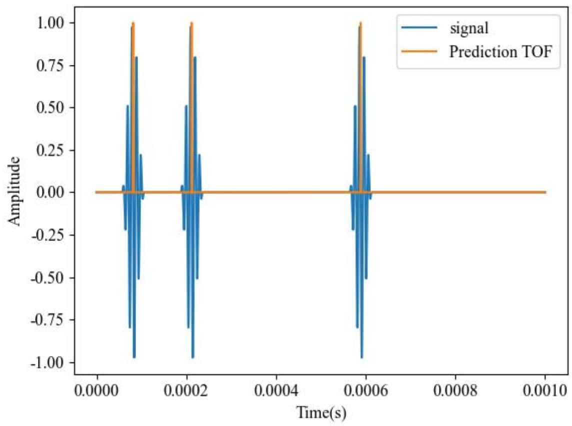
The testing results are presented in the table 2. In the single-wave packet mode, there is little difference in the training results between the CAE and FCAE models. Due to the long length of the data, reaching an overall training accuracy of around 85% is the best achievable result. In the multi-wave packet mode, the original CAE, which directly learns time information, struggles to effectively recognize situations where wave packets overlap. In contrast, the FCAE simultaneously learns both time-domain and frequency-domain information, allowing for better distinction in cases of wave packet overlap and achieving higher accuracy. After predicting the TOF for the signals in Figure 4 and compensating for dispersion according to Equation 7, the results are shown in Figure 5. The compensated signals exhibit a re-compressed wave packet width, achieving distinguishability of Lamb wave signals.



(a) Single wave packet



(b) Double wave packet



(c) Triple wave packet

Fig. 5: The compensation signal

4 Experimental Verification

Set up an experimental platform for Lamb wave signal acquisition as shown in Figure 6. The experiment involves generating hanning window-modulated sinusoidal wave signals using an air-coupled ultrasonic Lamb wave excitation and reception system. Four piezoelectric sensors are used for both excitation and signal reception. The excitation signal is fed into a power amplifier, and the signal is received by the excitation-reception system, followed by data processing on a computer.

The experiment is conducted on a square 304 stainless steel plate with a side length of 0.4m and a thickness of 0.001m. The excitation signal is a Hanning window-modulated sinusoidal wave with a duration of 3 cycles. The positions of several sensors and the location of the defect are shown in the table 3. Using several sensors to sequentially transmit excitation signals and employing other sensors to collect scattered signals, six sets of data are collected for validation. Due to the reciprocity of the propagation paths, six sets of data are gathered for test. The training data is generated through simulated methods. The experiment is conducted on a square 304 stainless steel plate with a side length of 0.4m and a thickness of 0.001m. The excitation signal is a Hanning window-modulated sinusoidal wave with a duration of 3 cycles.

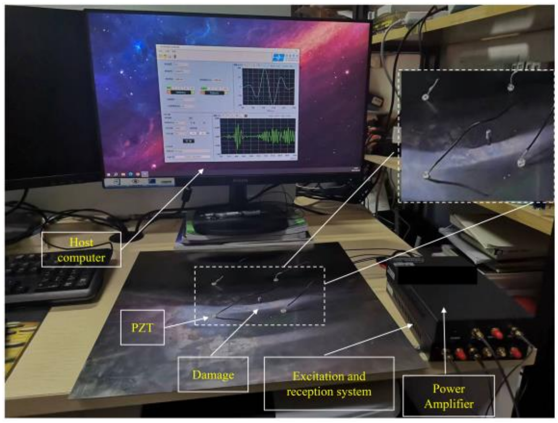


Fig. 6: The Convolutional Autoencoder

Using several sensors to sequentially transmit excitation signals and employing other sensors to collect scattered signals, six sets of data are collected for validation. Due to the reciprocity of the propagation paths, six sets of data are gathered for test. The training data is generated through simulated methods.

Table 3: Sensors and defect positions

	Location(X)(mm)	Location(Y) (mm)
PZT 1	250	250
PZT 2	250	150
PZT 3	150	150
PZT 4	150	250
Damage	210	225

Similarly, using the Dispersion Calculator, obtain the dispersion curves of the experimental steel plate and generate simulated data of the same specifications. Then, input the simulated data into the network model for experimentation, followed by testing with the experimentally collected data.

The six sets of scattered signals collected are shown in the figure 7. After propagating over a certain distance, the width of the wave packet gradually extends, indicating the phenomenon of dispersion. Considering that the collected signal mainly contains two wave packets, a model with dual wave packets is chosen for training. The TOF is determined by selecting the coordinates of the two maximum values in the output results，the red line in the graph represents the actual TOF calculated after computation.

The collected signals are input into the model for testing, and the signals are dispersion-compensated according to equation 7. The results are shown in the figure 8, where the red lines represent the predicted TOF, and the blue lines represent the signals after dispersion compensation.

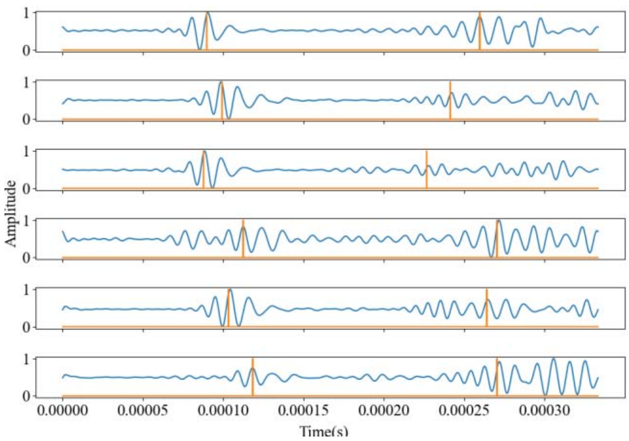
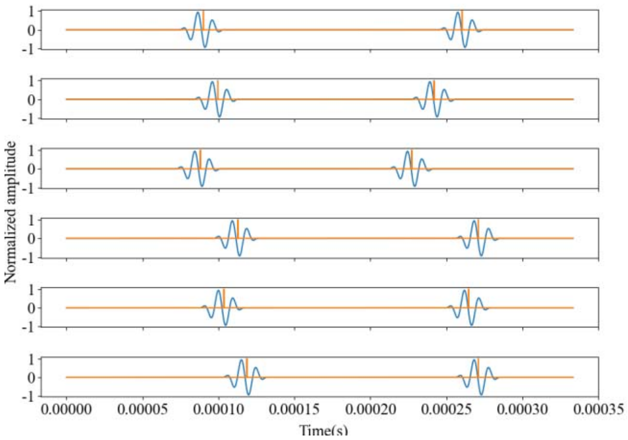
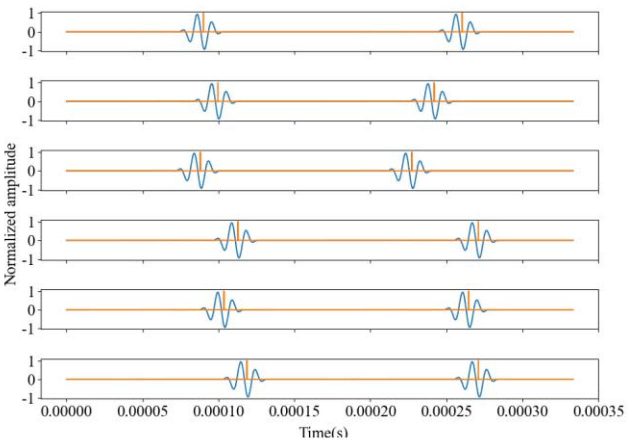


Fig. 7: The collected signals



(a) CAE



(b) FCAE

Fig. 8: The compensation signals

Figure 8 illustrates the application of two network models on actual data. In both methods, FCAE predicts TOF values closer to the true TOF. In the first wave packet, the predicted results of both methods are within an acceptable range. However, in the second wave packet, CAE predicts values with a significant deviation from the true values. This is because the signal at this point contains multiple reflected waves, and the CAE network, which only analyzes time-domain information, struggles to distinguish them. In contrast, the FCAE network, considering both time and frequency information, exhibits higher robustness.

5 Conclusions

The Lamb wave signal finds extensive applications in the industry; however, its dispersion phenomenon hampers its further utilization. Considering the frequency-dependent nature of dispersion, this paper proposes a Fourier-based convolutional autoencoder (FCAE) model. The Fourier basis is employed to extract time-frequency information, and the convolutional autoencoder establishes a connection between the extracted features and the TOF. In contrast to traditional autoencoders, which directly map time-domain information to TOF, the proposed FCAE model better meets the requirements of dispersive signals. The effectiveness of the proposed method is validated through subsequent simulations and experiments. Particularly, in scenarios involving multiple wave packets, the FCAE model exhibits significant performance improvements compared to traditional autoencoders.

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