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FilterNet: A CNN-RNN based filter model used for raw tunnel lining GPR data

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ABSTRACT

Ground-Penetrating Radar (GPR) technology, with its characteristics of being fast, non-destructive, and high-resolution, has become an important tool for detecting underground structures. However, GPR data inevitably suffer from environmental noise and electromagnetic interference during the acquisition process, leading to decreased data quality and increased complexity in data processing. Traditional filtering algorithms have limitations such as low discrimination between noise and signal, poor adaptability, and inability to process data in real time. This paper proposes a filtering model based on deep neural networks, called FilterNet. FilterNet combines Convolution Neural Networks (CNN) and recurrent neural networks (RNN) for processing multi-channel data. It can perform end-to-end filtering directly on the raw tunnel lining GPR data, achieving functions such as removing air reflection waves, denoising, and automatic gain. Using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) as statistical indicators, it is shown that the FilterNet model improves filtering precision. The SSIM of all three models is 0.997, and the PSNR of FilterNet1D and FilterNet are 19.06 and 19.41, respectively. Furthermore, tests on the model's processing efficiency indicate that FilterNet requires less memory and is more efficient than the UNet model. FilterNet's parameters are only 48 % of those of UNet. Its GFLOPS (Giga Floating Point Operations Per Second) is only one-third of UNet's, and it can process data in real time. Additionally, FilterNet performs exceptionally well in suppressing random noise.

1. Introduction

With the development of railway construction, the demand for accurate exploration of underground spaces has been increasing (Yang et al., 2023). Ground-penetrating radar (GPR) technology, known for its speed, non-destructive nature, and high resolution detection, offers an effective method for precisely exploring shallow underground structures. GPR works by emitting high-frequency electromagnetic waves and receiving the reflected signals, which reveal the distribution of underground materials and help detect abnormalities or defects in underground structures. This makes GPR useful in railway subgrade inspections (Xu et al., 2018; Liu et al., 2023).

However, GPR data are often affected by environmental noise, electromagnetic interference, and other factors, which can decrease the data quality and complicate interpretation and analysis (Yang et al., 2023). Therefore, improving the signal-to-noise ratio (SNR) of GPR data and effectively suppressing noise is critical to enhance the effectiveness of GPR technology (Liu et al., 2024). There are various types of noises in GPR data, such as random noise data (Chicarella et al., 2014), strong noise reflected by the sleeper (Liu et al., 2024). And we also need to enhance the weaker reflected signals from deep interfaces (Oskooi et al., 2018). Usually we need different methods to filter the noises and enhance the signal.

Traditional GPR data filtering algorithms, such as the Fourier transform and wavelet transform, have clear physical meanings and can be used for data filtering without training a model. Oskooi et al. (2018) reviewed various signal processing techniques for eliminating or weakening random noise in GPR data, including the curvelet transform, non-local mean, median, and mean filters, and compared their performance in synthetic and actual GPR data. They found that the curvelet transform and non-local mean are more effective than the other methods. Zhang et al. (2021) explored the application of a bilateral filtering algorithm in GPR data denoising processing and verified, through simulation and field test data filtering, that the bilateral filtering algorithm

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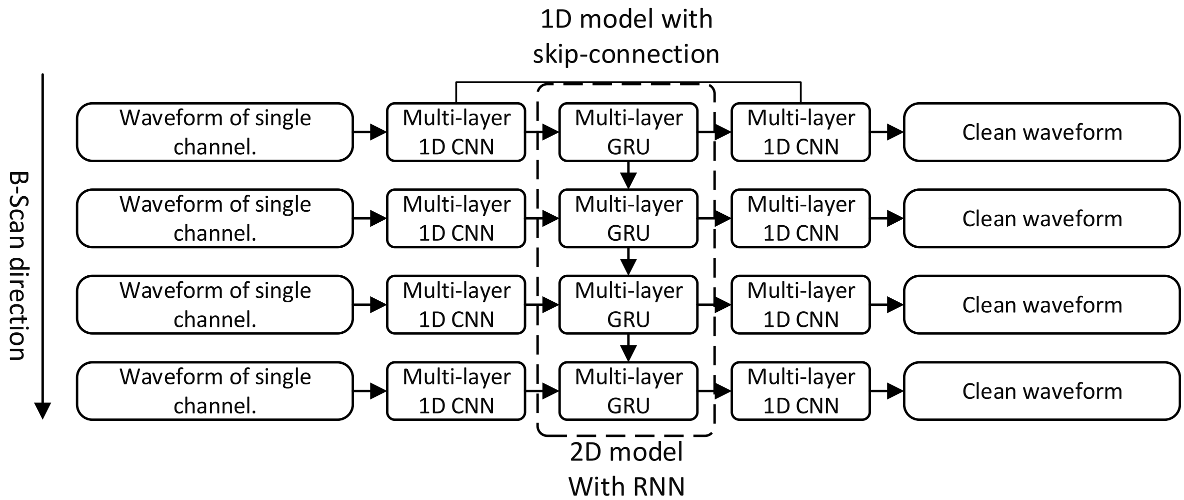

Fig. 1. FilterNet neural network architecture (FilterNe1D does not include RNN).

could effectively remove White Gaussian Noise and improve data quality. Cheng et al. (2024) proposed a time-varying bandpass filter based on the local maxima multiple synchrosqueezing transform for reducing non-stationary random noise in GPR data. Zhu et al. (2017) proposed a GPR signal denoising technique based on wavelet transform, which utilizes the excellent time-frequency localization characteristics of wavelets to decompose and reconstruct a single-channel radar signal, thereby improving the recognition ability of tunnel lining images and the accuracy of radar signal interpretation. Traditional filtering algorithms employ fixed feature functions, most of which are designed to eliminate random noise.

Therefore, machine learning methods, which can build a feature function from data, have been developed. Xue et al. (2019) proposed a GPR signal noise suppression method based on ensemble empirical mode decomposition (EMD) and permutation entropy (PE), by calculating the PE of each intrinsic mode function (IMF) and using a global threshold to distinguish between noise IMF and target IMF. The method can effectively remove the noise. He et al. (2020) shows that the VMD-based method can locate the underground utilities as well as highlighting the corresponding time-frequency features. Li et al. (2022) proposed an adaptive GPR denoising method based on the fast independent component analysis (Fast ICA) and wavelet transform modulus maxima multi-fractal spectrum. The method can separate the anomaly information that was previously buried by noisy signals, offering higher stability and convenience compared to the traditional method. FastICA, EMD and VMD are generalized linear models, whose feature functions are simple.

Table 1
The parameters of FilterNet.

Submodule	Layer	Kernel size	Input feature	Output feature	Activate function
Encoder	CNN	7	1	8	ReLU
	CNN	7	8	8	ReLU
	CNN	7	8	16	ReLU
	CNN	7	16	16	ReLU
	CNN	7	16	32	ReLU
	CNN	7	32	32	ReLU
	CNN	7	32	64	ReLU
RNN layers	GRU	–	64	64	Tanh
	GRU	–	64	64	Tanh
Decoder	CNN	7	64	32	ReLU
	CNN	7	32	32	ReLU
	CNN	7	32	16	ReLU
	CNN	7	16	16	ReLU
	CNN	7	16	8	ReLU
	CNN	7	8	1	Sigmoid

They cannot handle more complex data, such as directly processing raw GPR data to final filtered data.

Therefore, some non-linear filtering algorithms, based on a Deep Neural Network (DNN), have been used more recently. Temlioglu and Erer (2021) build a Convolution Neural Network (CNN) (LeCun et al., 1998) based autoencoder to filter GPR data. The result shows that autoencoder method has better performance than decomposition models. Huang and Zhou (2023) proposed a multi-noise self-supervised denoising DNN model, which addresses the problem of multiple composite noise in GPR images. Liu et al. (2024) introduced UNet, which is built by CNN and used in biomedical image segmentation (Ronneberger), suppressing the strong noise of railway subgrade detection, and effectively improved the SNR by training on real railway subgrade structure data sets. The UNet can also be used in reconstructing the missing channel data in GPR data (Rohman). Lin et al. (2023) show that GPRNet for A-Scan data can be used in railway subgrade detection in real time. However, it cannot get the spatial feature in B-Scan data. When processing two-dimensional B-Scan data using a deep neural network, the inputs are multiple-channel data, which may cause two problems in the processing process. The first is a low processing efficiency, as the DNN model has more trainable parameters than traditional algorithms, and the processing speed is slower. The second is that the real-time processing goal cannot be achieved.

Tunnel lining GPR data denoising methods have improved data quality to varying degrees; however, there are still limitations, including poor discrimination between noise and signals, limited adaptability to complex environments, and the inability to process data in real-time. To solve the noise suppression problem in GPR data processing, we have built a filtering DNN model based on CNN and RNN called FilterNet. Our model can directly process the raw GPR data collected and output the filtered data directly. At the same time, our model is smaller and more suitable for real-time processing compared to the UNet model.

2. Method

2.1. *The architecture of FilterNet*

CNN is often used to process waveform and image data. The B-Scan sections are two-dimensional data, which are suitable for a 2D CNN. Liu et al. (2024) used 2D CNN to build a UNet to process the original collected data. 2D convolution is suitable for processing non-real-time data, which needs to convert B-Scan section into 2D image. And the UNet has a higher risk of overfitting when the training data is limited. Here, we designed FilterNet to process GPR B-Scan data, which has the following features: high processing efficiency, real-time GPR data

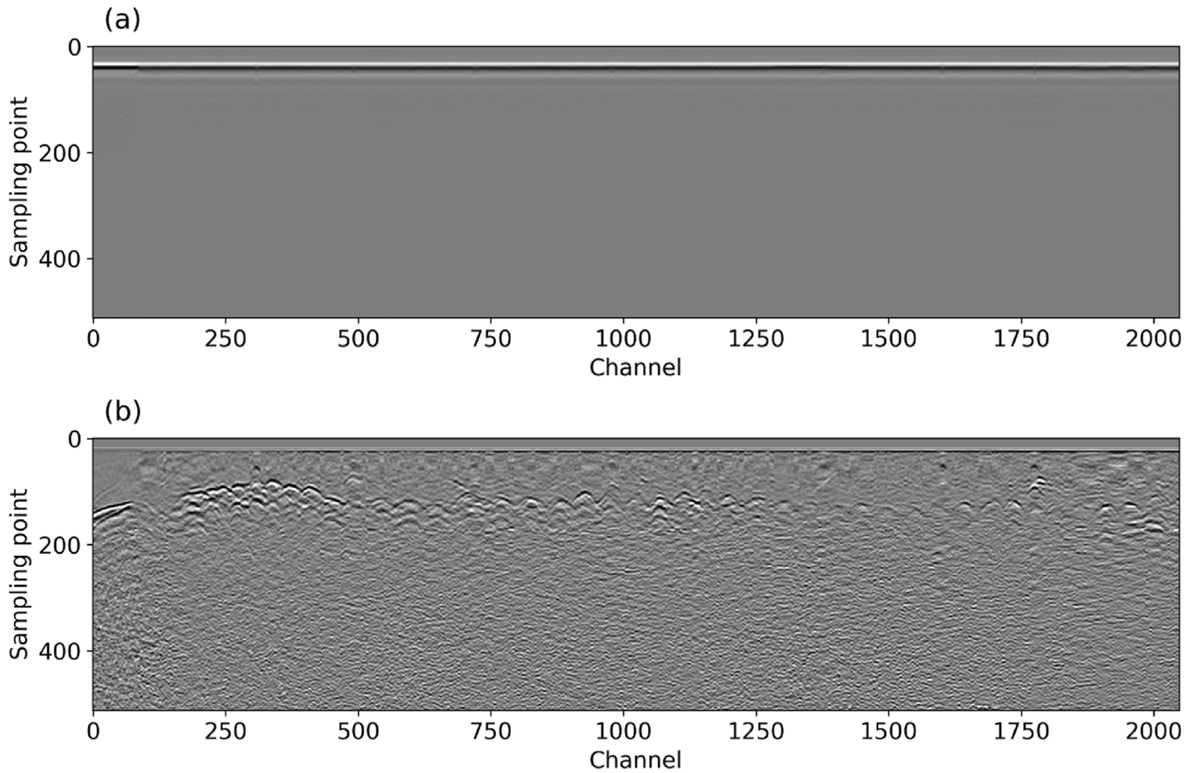

Fig. 2. Input data (a) and label data (b) during the training process.

filtration, fewer trainable parameters, trained with a small amount of data. We designed FilterNet, which conbines a CNN and Recurrent Neural Network (RNN) layers called GRU (Cho, 2014), to process multi-dimensional data. To compare with the FilterNet, we removed the RNN layers from FilterNet and added skip-connection in the model. This formed a new model called FilterNet1D, which is used for single channel data. The structure of FilterNet is shown in Fig. 1.

As shown in Fig. 1, we designed a filtering structure based on a 1D multi-layer CNN. We utilize CNN to build an encoder and a decoder. The encoder is used to process the original 1D waveform from a channel directly and obtain the waveform feature vector v. The length of a channel must be fixed to 512. The decoder is used to decoder the waveform feature vector v into filtered data. In FilterNet1D, we did not add any other structures. Instead, like UNet, we incorporated skip connections to accelerate the model's convergence (Rohman et al., 2021). FilterNet input v into GRU layers during processing, enabling the model to handle 2D B-Scan profile data. Ultimately, the output of the model is the filtered waveform.

The detailed structure of the model is presented in Table 1. Since FilterNet has an RNN to ensure accuracy, the length of the feature vectors in the convolutional layers is shorter, thus reducing the number of trainable parameters. As FilterNet1D has a skip connection, the length of the vector input in the encoder part is longer. Both final outputs are passed through a Sigmoid activation function to constrain the output to (0, 1).

2.2. Training data

In some works, theoretically generated data are used. However, synthetic data often differ significantly from real data, rendering the trained model unusable. Therefore, we use actual collected data for model training and testing. Our data, which are intended to detect the quality of tunnel lining, are collected from the lining inspection data of 15 tunnels along Yizhan Railway Yilou Section, including Liujia Tunnel and Su Youchong Tunnel. The section starts from Yiyang East Station in the north and ends at Loudi East Station in the south. It passes through He District and Taojiang County in Yiyang City, Ningxiang City in Changsha City, Xiangxiang City in Xiangtan City, and the Economic Development Zone and Louxing District in Loudi City. Its geographical coordinates roughly range from latitude 27°40′N to 28°30′N, and longitude 111°50′E to 112°20′E. The goal of FilterNet is to process raw waveform data directly (Fig. 2a). It can output the filtered waveform after removing air reflection wave, noise reduction and automatic gain adjustment (Fig. 2b). The original GPR data is affected by air reflection wave, and the reflection waves are suppressed. Thus, the effective signal is difficult to identify. In general, the model used for GPR filtering needs to remove air reflection wave first, while the goal of our model is to achieve end-to-end output, i.e., directly processing raw waveform data and directly outputting the final filtered result. Using this direct input method with raw collected signals can greatly shorten the GPR post-processing workflow and improve the overall automation level. The input data of the model undergoes only normalization during preprocessing, without any additional processing. The specific formula is as follows,

$$\hat{x} = \frac{x - \max(x)}{\max(x) - \min(x)} \tag{1}$$

where $\hat{x}$ are the normalized data, x are the original data, and $max()$ and $min()$ are the maximum and minimum value functions, respectively.

We use Reflexw to process raw waveform and get the label data d (Fig. 2b). Reflexw is a professional data post-processing software widely used in GPR data analysis. It provides a series of data processing functions, including data import, gain, filtering, editing, etc.

2.3. Real-time inference process

FilterNet must process raw GPR data in real-time. The 1D model processes single-channel data as the processing unit, and thus its processing process is relatively simple. We only need to input real time 1D channel data into FilterNet1D. The 2D model is used to process two-dimensional data, and thus the processing process needs to be carefully

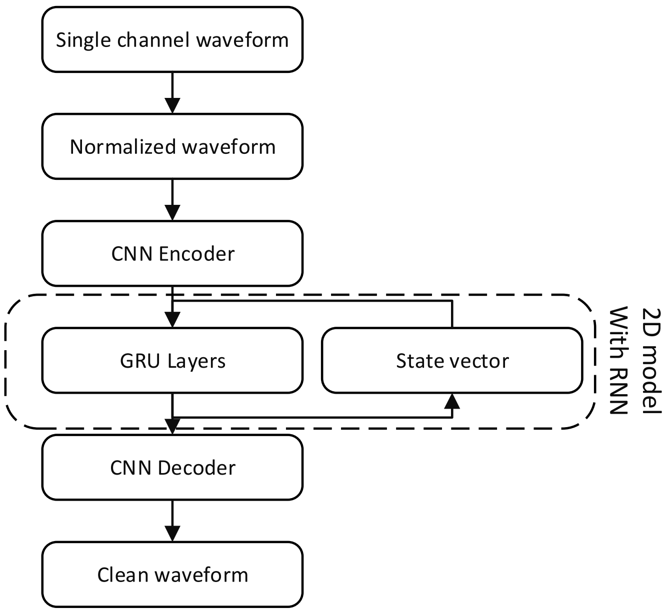

Fig. 3. The infer process of our model.

adjusted. The processing flow is shown in Fig. 3.

As shown in Fig. 3, the FilterNet needs to normalize the single-channel data during inference, which transforms the data into the interval of (0, 1), the input is fed into the encoder of the convolutional neural network to obtain the feature vector v. The feature vector v and the state vector h_{t-1} of GRU are input into the recurrent neural network to obtain a new state vector h_t of the current channel t. The state vector h_t is decoded into the desired filtered waveform by the decoder. During this process, the state vector h_t contains information on the current channel and the previous channels, and thus it is a 2D model for B-Scan data.

3. Performance analysis of FilterNet

3.1. Single data analysis

We tested a single file and used a test fold of 2048 lines with GPR single-line data length of 512. The detection results are shown in Fig. 4.

It can be observed that in the raw data (Fig. 4a), energy is mainly concentrated in the reflection wave portion, making the underground reflection waves nearly invisible. The label data (Fig. 4b) contains a significant amount of random noise. In the real data, the reflection wave is stronger than the simulated data by Liu et al. (2024). However, the results indicate that FilterNet can effectively filter out most of the noise data (Fig. 4c). Theoretically, the neural network output data should be consistent with the label, but as shown in Fig. 4d, the random noise is also suppressed. This is because high-frequency noise is randomly generated, with values that are either positive or negative, whereas deep neural networks tend to yield an average result, i.e., one without random noise. From this perspective, the neural network can not only highlight the reflection wave as we expect, but also effectively suppress random noise, which is an advantage that traditional filtering algorithms do not have. The outputs of the 1D and 2D model are slight different. The 1D model still has noise, but it is primarily lateral. In contrast, the 2D model demonstrates better performance in suppressing random noise.

3.2. The accuracy of FilterNet

In the model accuracy test, we compared three models, i.e., FilterNet1D, FilterNet and UNet used by Liu et al. (2024). The statistical parameters include PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index). The calculation method of PSNR is,

$$PSNR(x,d) = 20\log\left(\frac{MAX_I}{RMSE(x,d)}\right) \tag{2}$$

where x and d represent the filtered waveform and the labeled waveform, respectively, RMSE (x,d) is the mean square error between the true value and the filtered value, MAX_I is the maximum value of the graph, and PSNR is used to measure the SNR of the filtered data, with a higher value being better. The SSIM calculation method is,

$$SSIM(x,d) = \frac{(2\mu_x\mu_d + c_1)(2\sigma_{xd} + c_2)}{\left(\mu_x^2 + \mu_d^2 + c_1\right)\left(\sigma_x^2 + \sigma_d^2 + c_2\right)} \tag{3}$$

SSIM is used to measure the structural similarity between two images, and the closer SSIM is to 1, the better. The statistical results of each model are shown in Table 2.

The accuracy differences among different models are small. The accuracy differences are not significant during the use process. Both FilterNet1D and FilterNet can complete real-time detection tasks. As expected, FilterNet1D has a lower accuracy because it only processes single-channel data, but in actual testing, its accuracy is consistent with UNet. This means that single-channel data already contain sufficient information about the signal. We chose some filtered results for plotting, as shown in Fig. 5.

Although the SSIM and PSNR values of the model are similar, there is a significant difference in visual perception. This is because most of the data in our model are the mean (gray), and the signal is concentrated in the shallow layer. This leads to easy obtaining of high values in actual testing. By comparing Fig. 5b and d, FilterNet1D and FilterNet are statistically similar, but there is a difference in the scanning direction, with FilterNet filtering out more horizontal texture. This is because FilterNet's model can learn horizontal features. This is consistent with UNet, which also processes 2D models. The contrast of the signal in the UNet model is lower during the processing.

3.3. Computation efficiency test

We calculated the theoretical computational complexity of the model, including Floating Point Operations (FLOPs) and the number of the model's trainable parameters. We also measured the actual computation time of the model on Xeon(R) Platinum 8255C, and the results are presented in Table 3.

From the statistical results, in the actual processing process, FilterNet has the slowest processing speed, because the RNN model is difficult to parallelize the model, which limits the processing efficiency of the model on multi-core CPUs according to the number of cores. In contrast, on processors with weaker processing capabilities and fewer cores, such as ARM architecture, the theoretical processing speed can be evaluated by referring to GFLOPS (Giga FLOPs). The larger the number, the slower the theoretical processing speed. FilterNet only needs 3.21 GFLOPS in the processing process, which is only 1/3 of UNet. At the same time, FilterNet has only 107.1 K trainable parameters, which means that the model can complete the processing with minimal memory. UNet has 115.1 K more trainable parameters than FilterNet, and it is a non-real-time processing model that needs to input multiple slices of data at the same time, which means that more memories are needed to complete the calculation. The FilterNet model requires only one slice of data, which means it needs less memory during processing.

3.4. Model generalization ability test

Different from traditional methods, FilterNet, as a DNN method, relies on the training dataset, which means that FilterNet will achieve a higher precision when processing the data similar to the training dataset. However, it will get a poor result when the data are different to the training dataset. We test the generalization ability by applying the FilterNet on two types of data, i.e., the tunnel lining GPR data record from

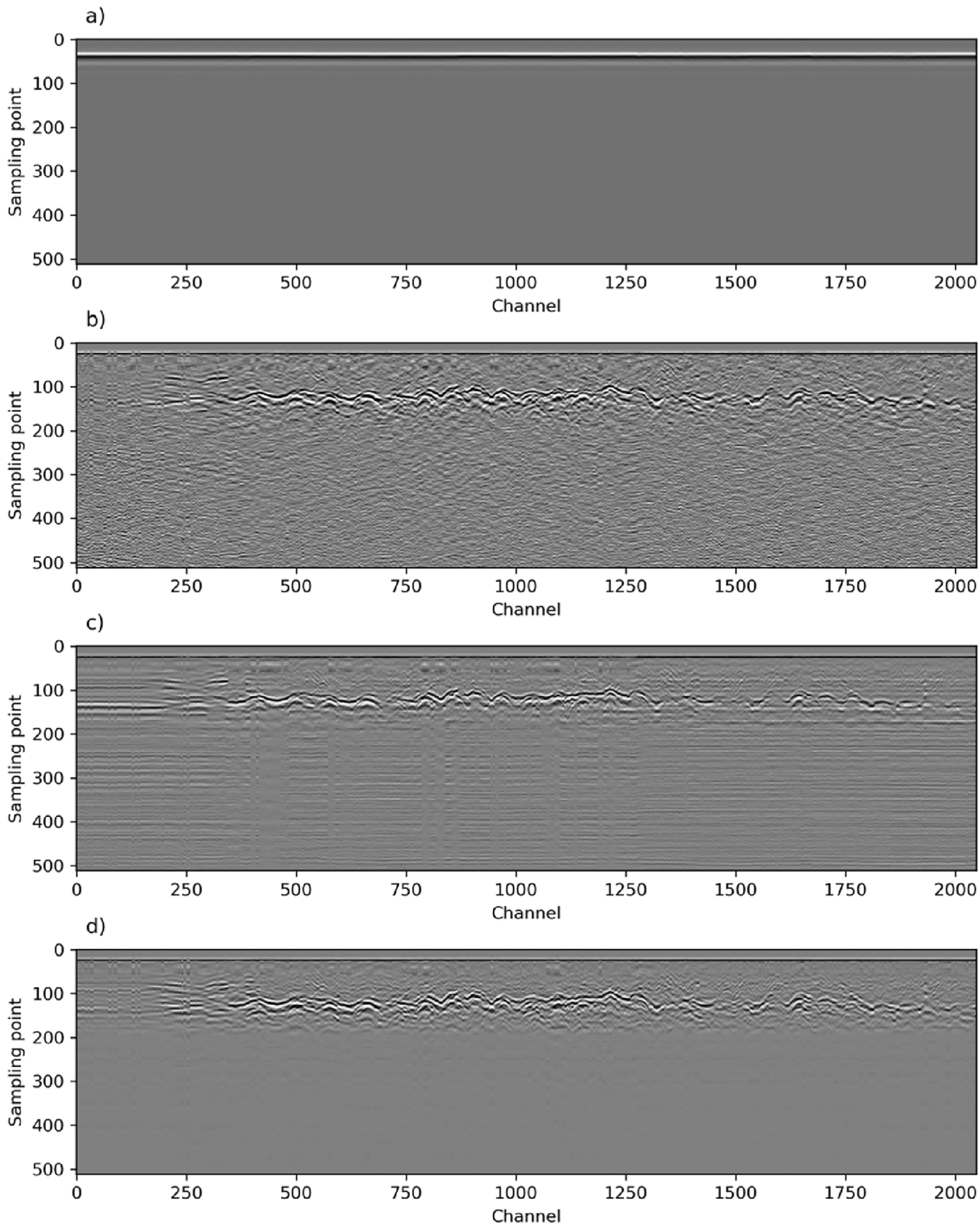

Fig. 4. Model processing result, (a) original input data, (b) label data, (c) FilterNet1D result, and (d) FilterNet result.

XiangShan tunnel located in LongZhang section, and generated pipeline reflection GPR data.

We can see from Fig. 6 that the GPR data from XiangShan tunnel have more background noise than the training dataset. And the DNN models can effectively remove the noise. The ability of FilterNet1D to remove background noise is weaker than other models. Because FilterNet1D can only process a single channel of data, which cannot refer to other channels.

Table 2
Statistics of different model parameters.

Model Name	PSNR	SSIM	Real time processing
FilterNet1D	19.06	0.99709	Y
UNet	19.33	0.99702	N
FilterNet	19.41	0.99701	Y

The test on the generated pipeline reflection GPR data is shown in Fig. 7. We added random Gaussian noise to the generated pipeline data.

We can see that all the models get poor results as the models are not trained on the pipeline data. The FilterNet1D model can get the shape of the reflected wave from the pipeline. We can hardly get the ideal result

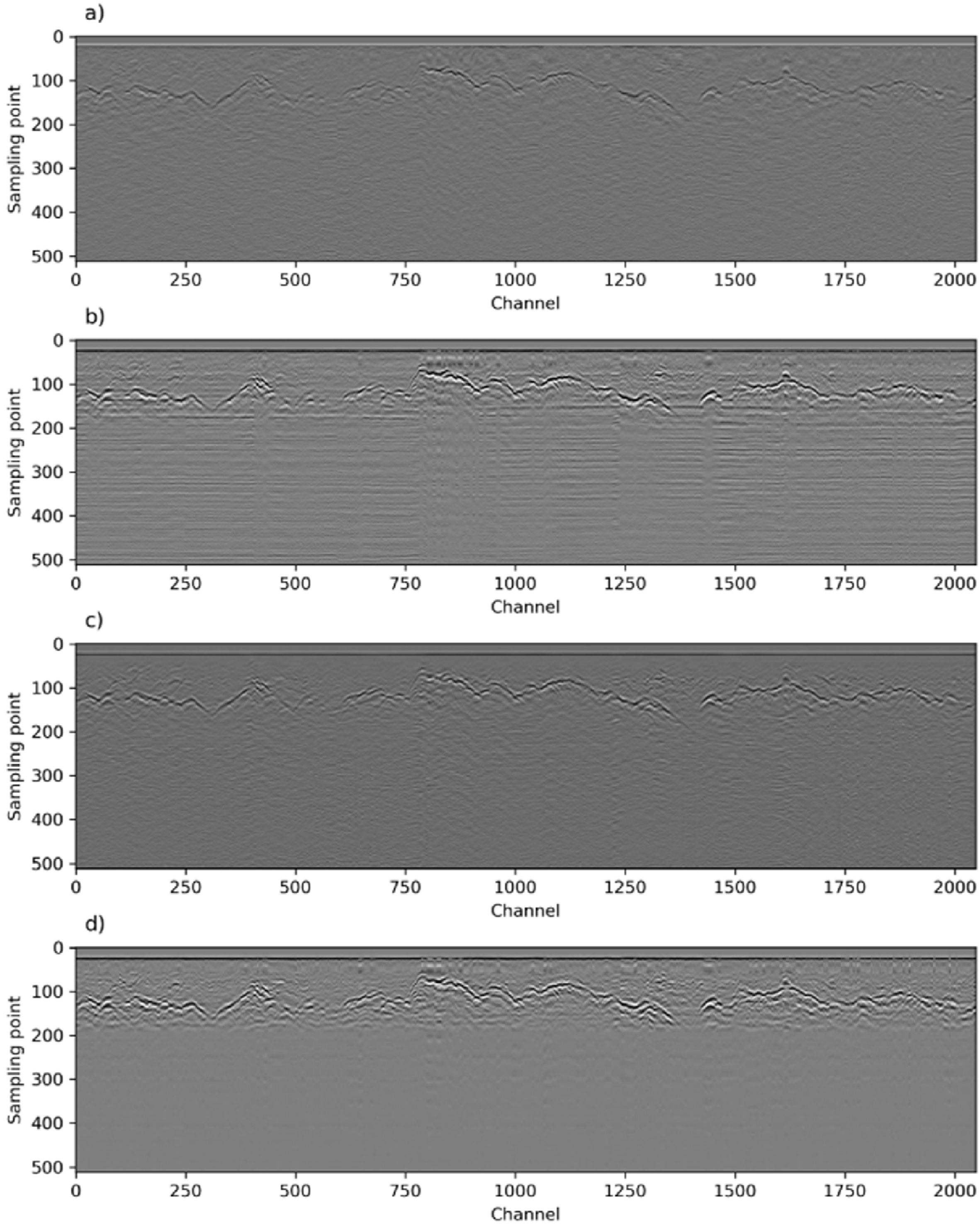

Fig. 5. Example of filtering effects, (a) labeled data, (b) FilterNet1D filtering result, (c) UNet filtering result, and (d) FilterNet filtering result.

from UNet and FilterNet. This is because the UNet and FilterNet have better fitting abilities, which leads to weak generalization ability.

Table 3
Model computation accuracy and model size statistics (2048 channels).

Model Name	Number of training parameters (K)	GFLOPS	Infer time (ms)
FilterNet1D	137.1	8.45	179.1
UNet	222.2	10.78	214.3
FilterNet	107.1	3.21	261.3

The test results indicate that to adapt to more data, we need to utilize a wider range of data types for transfer learning training.

4. Discussion

It can be found that deep learning neural network models can take the original GPR data as input. This represents that the deep learning model can completely replace the direct wave removal, filtering, gain adjustment and other pre-processing works. Through the comparison, both the FilterNets can complete the filtering task. At the same time, as the neural

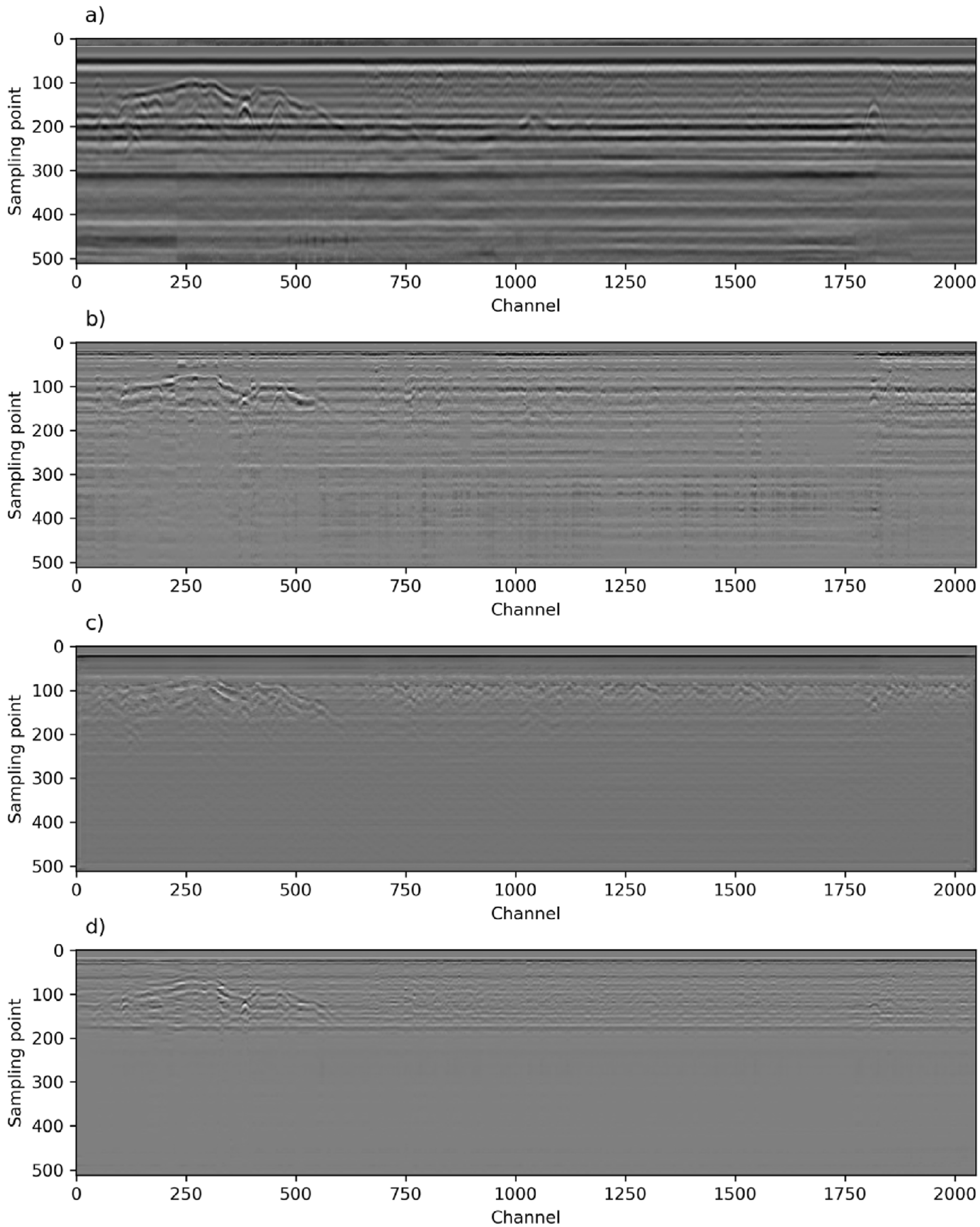

Fig. 6. The filter results of tunnel lining GPR data from XiangShan tunnel, (a) labeled data, (b) FilterNet1D filtering result, (c) UNet filtering result, and (d) FilterNet filtering result.

network will get an average effect, although random noise is not filtered as a label, FilterNet has a better suppression effect on deep high-frequency noise in actual use. However, the 1D model has difficulty in filtering horizontal noise. The 2D model has a better horizontal noise filtering effect than the 1D model.

We added two types of noise to the model for generalization performance testing. The first type was adding a direct wave-like noise to the middle of the data, and the second was adding a Gaussian noise with a maximum amplitude of 1% to the data. The test results are shown in Fig. 8. After adding the direct wave noise, UNet could no longer output normally (Figs. 8c–1). FilterNet could output signal, but the signal was weak (Figs. 8e–1). FilterNet1D could still output normally, but it needed to filter out the direct wave. This is because we only included one group of direct waves (horizontal background noise) in the training process, and we could not handle it when the number exceeded this. FilterNet, which inputs single-channel data in sequence, has better tolerance for this type of noise. After adding the Gaussian noise, the performance of all models has decreased. UNet, which uses CNN to process, has a high risk

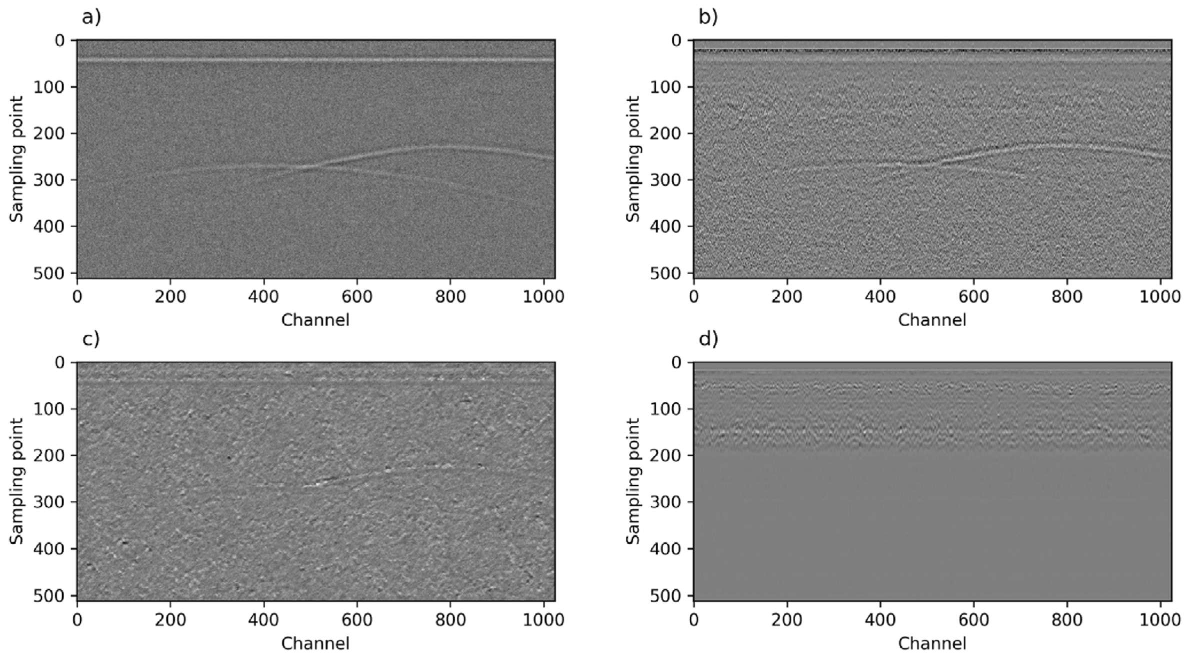

Fig. 7. The filter results of generated pipeline data with added random Gaussian noise, (a) Labeled data, (b) FilterNet1D filtering result, (c) UNet filtering result, and (d) FilterNet filtering result.

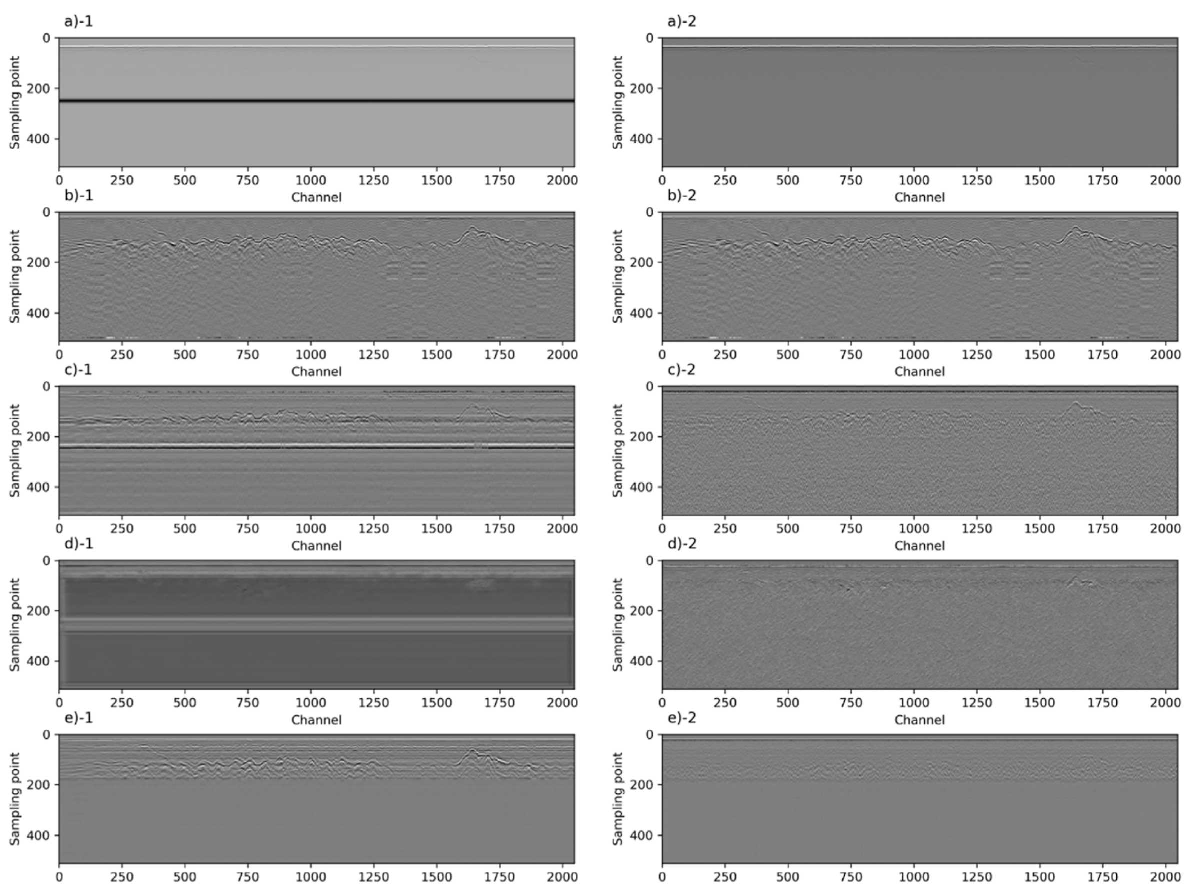

Fig. 8. Filtering results after noise addition. 1 is the result of adding direct wave filtering, and 2 is the result of adding normal distribution noise filtering. (a) Original image, (b) Labeled image, (c) FilterNet1D model filtering result, (d) UNet2D model filtering result, and (e) FilterNet model filtering result.

of overfitting and lower accuracy when the data and training data are different, i.e., the model has weak generalization ability. FilterNet, which also added two-dimensional training, has a stronger generalization ability because its model includes RNN. It can output part of the waveform in Figs. 8e–2, but the signal is weak. FilterNet1D, which is also a CNN, can still see part of the reflected waveform because it processes more signals in a single channel. Among the models, FilterNet1D has the best generalization ability, and UNet has the weakest generalization ability.

5. Conclusion

We designed a filtering model that can be directly applied to raw GPR data, called FilterNet. FilterNet includes two types of models. The first type only contains a CNN, called FilterNet1D, which can filter single-channel data. The second type contains both a CNN and an RNN, which can process multi-channel data, called FilterNet. Both models can filter the GPR data collected in real-time and output the filtered results end-to-end. FilterNet has the following three advantages.

1. Our FilterNet can output end-to-end, shortening the processing flow from direct wave removal, filtering, and gain adjustment.
2. FilterNet models have a better suppression of random noise and can obtain the same results as manually processed data. At the same time, FilterNet has a better generalization ability than UNet and can obtain results in noisy conditions.
3. The model can output in real-time, and the theoretical computational efficiency is high. At the same time, the real-time processing process requires less memory, and only a small amount of memory is needed to complete the filtering task.

The code is available on https://github.com/cangyeone/filternet.

CRediT authorship contribution statement

Bang Zhang: Writing – review & editing, Writing – original draft, Resources, Methodology. **Yu-Qi Cai:** Writing – review & editing, Writing – original draft, Formal analysis. **Zi-Ye Yu:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Kai Li:** Writing – review & editing, Data curation.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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