Convolutional Neural Network based denoising method for rapid THz Imaging

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***Abstract*— We propose our own convolutional neural network (CNN) structure as a post-processing method for the rapid THz Imaging in Terahertz Time Domain Spectroscopy(THz-TDS). The experiment results show that our approach can greatly reduce the noise and artifacts in the collected under-sampled THz images, which in turn benefits the rapid THz imaging technique by allowing higher acquisition rates. In our setup, 5 times higher acquisition rates can be realized. Moreover, this approach needs no extra hardware cost, and since the training has been done offline, the processing time in practice can be ignored. To the best of our knowledge, this is the first time applying deep learning(DL) methods into rapid THz imaging technique, which would inspire researchers to explore more DL based applications and technologies for THz technique development.**

I. INTRODUCTION

with the great development of DL methods in recent years, CNNs receive more and more attention in image classification[1][2], identification[3] and image denoising[4], providing a promising approach for improving the THz image qualities in rapid THz image technique which usually suffers the bad reconstruction image quality.

Rapid THz imaging with a single-pixel detector works by projecting a set of spatial encoding masks onto the object, and THz pulse transmission through the object recorded by the detector, with post-processing method and image reconstruction algorithm. Details can be found in our group previous work[5]. The lack of THz dataset hinders the application of DL methods in THz regime. Here we build up our own THz image dataset, which is also the first THz image dataset that can be used for training the deep learning model, by THz rapid imaging technique and propose our own designed CNN model: a symmetric deep convolutional neural network (SDCNN) as post-processing method to remove the blurring artifacts and noise of the reconstructed THz images, which further allows the improvement of higher imaging speed.

II. METHODS AND RESULTS

The structure of the SDCNN can be separated into 2 stages. As shown in Fig.1. The network mainly employs convolutional layer (Conv2D) to extract information from the images and remove artifacts by using a set of trainable filters with different receptive field. The first stage uses 32 filters (5×5×1) and 64 filters(3×3×32) while the second stage uses 64 filters(3×3×128) and 32 filters(3×3×64) with a 128 filters(3×3×64) layer in between. At the end of the network, there is a Conv2D filter(1×1×1) to reconstruct the image as designed size. To speed up the training process, each Conv2D layer is followed up by a Batch Norm layer, the ReLu function has been adopted after each Batch Norm layer to add non-linear activation. The Max-Pool layer is used to reduce the image size and increase the tolerance to the noise. On the contrary, the Up Sampling layer increase the image sizes and restore the images resolution back to the original in the second stages. Inspired by the ResNet structure[6], skip connections are implemented to pass information from the first stage directly to the second, which would recover important details and pass the gradient information to much deeper layers. The network has been well designed and fine tuned to improve the image quality. After reconstructing under-sampled THz images, the images are sent to SDCNN for quality improvement. Once the training is off, this quality improvement process will cost computational time at an ignorable level. A widely accepted index for evaluating the image quality is structural similarity index measurement (SSIM)[7]. As shown in fig.2, intuitively, the image quality improvement by our proposed SDCNN is very obvious, which can also be reflected quantitively by the SSIM value with the increase reaching to 0.2.

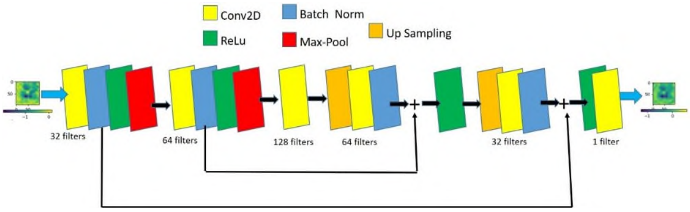

Fig. 1. The structure of the SDCNN.

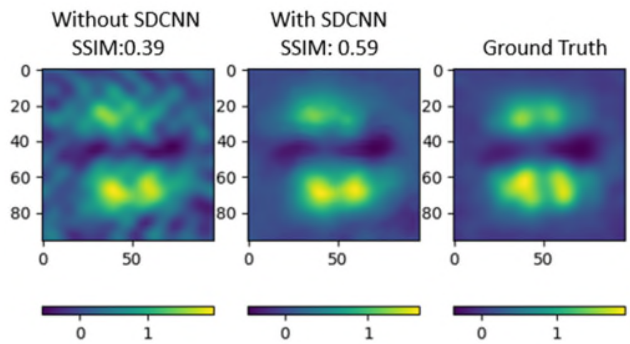

Fig. 2. THz images for comparison. The SSIM is calculated between data without SDCNN/ with SDCNN and ground truth. Ground truth is the standard images the output images try to approximate.

III. CONCLUSION AND FUTURE WORK

Our proposed network shows good effect on improving the under-sampling THz image quality. Combined with other new contributions, we finally develop a single-pixel THz imaging technique 10 times quicker than current commercial THz imaging systems with similar spectroscopic capabilities. The most interesting aspect of this work is that there is no inherently expensive equipment involved and the potential of achieving faster acquisition is restricted by noise and not equipment capabilities. Future work will focus on explorations of introducing more DL methods into THz technique and optics design for more specific applications such as skin imaging. Our full work will be published soon, welcome to follow it if you are interested.

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