CNN-based Super-resolution Full-waveform LiDAR

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Abstract(35-words): Instead of using multiple sets of measurements, we discuss a CNN with one set of data to obtain temporal super-resolution in full-waveform LiDAR. The super-resolution results can enhance further waveform decomposition or classification performance.

1.Introduction

Because full-waveform LiDAR can receive the whole digitized backscattering laser pulse signal, its data contain more information about an object compared to traditional LiDAR [1]. Since the first system is announced in 2004, many data processing algorithms [1] have been designed for analyzing waveform shape, segmenting and modeling an object, or doing classification. However, a few works have focused on improving system ranging resolution, which is an importance parameter in full-waveform LiDAR. Besides restricted by system hardware, to improve ranging resolution means to collect more data, which will cause higher requirement to system receiver and data storage device. Without using more sophisticate hardware and acquiring more data, we study a CNN-based algorithm to improve system resolution in this paper. We also expect that, using this algorithm can help to improve the performance of follow-up research works.

2.Algorithm architecture

Inspired by the excellent performance of CNN in research fields such as computer vision and pattern recognition, we apply CNN into LiDAR data processing. Our algorithm mainly contains following parts: data pre-process, batch-data input, first convolution layer, multiple residual blocks [4], up sample layer, and the optimization part which connects the output data with the corresponding ground truth. Figure. 1 shows the whole architecture of our algorithm for network training. In network training, a pre-process part is designed for denoising and down-sampling the raw data. The process is an important part which seriously affects the result of the overall algorithm. Different pre-process methods were applied to different raw data. In our network, there are 17 convolution layers. Each convolution layer contains multiple 1-D kernels with size 3×1. The number of convolution kernels also changes while processing different raw data. Residual block was designed as following [4]:

$$X(n)\_in \longrightarrow Convolution \longrightarrow Relu \longrightarrow Convolution \longrightarrow X(n)\_out$$

The up-sample scale decides the super-resolution ratio of our algorithm. Default values can be set to 4 or 8. To prepare the training data, we generate the ground truth data using standard Gaussian functions. The parameters of the Gaussian functions such as the peak positions are extracted from massive raw full-waveform LiDAR data. As for optimization, L1 distance between ground truth and output data was defined as loss function. Stochastic gradient descent (SGD) and Adam optimizer are used in our algorithm. In the testing process, the network with the lowest loss value after the training is used to process full-waveform LiDAR database samples and output high resolution signals.

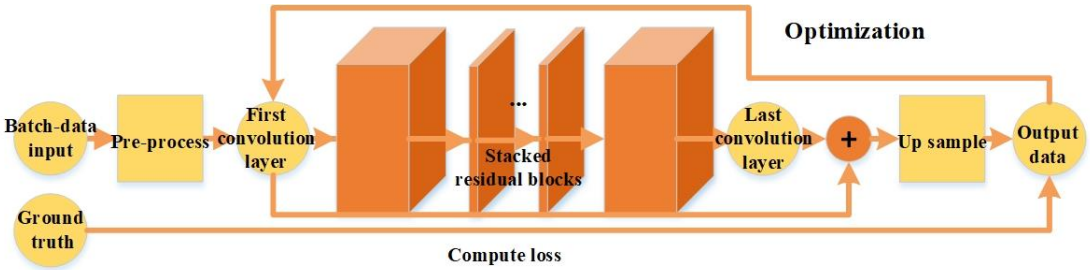

Figure. 1. The whole architecture of the CNN-based algorithm

3. Experimental

results

The full-waveform LiDAR data which we used for network training and testing came from the National Science Foundation's National Ecological Observatory Network (NEON). We extracted about 16700 waveforms from the slant LiDAR data (BART_201406217_FL09) obtained at the BART observation. Firstly, we estimated the feature parameters of the original full-waveform signals, such as the amplitudes, the positions of the peaks, and the full widths at half maximum of the waveforms. Then, we generated some standard Gaussian functions with these feature parameters as the ground truth data. By adding noise to the standard Gaussian functions, we get the simulated data, which is similar to raw data in the LiDAR database. Both of the simulated data and the ground truth data are divided into batches for training. Each batch contained 10 waveforms. After training, the network with the lowest loss is used for testing.

Figure 2 shows one original full-waveform LiDAR data and the output data with super-resolution upscale factor of 4. The original signal contains 256 sample points corrupted by noise. The sample time period in the original signal is 1ns, which means the system range resolution is 30cm. Using our CNN-based algorithm processing, the echo signal contains 1024 sample points. The sample period drops to 0.25ns. The ranging resolution becomes 7.5cm. The noise has been reduced. Some hidden peaks and valleys in the signal are easier to be found.

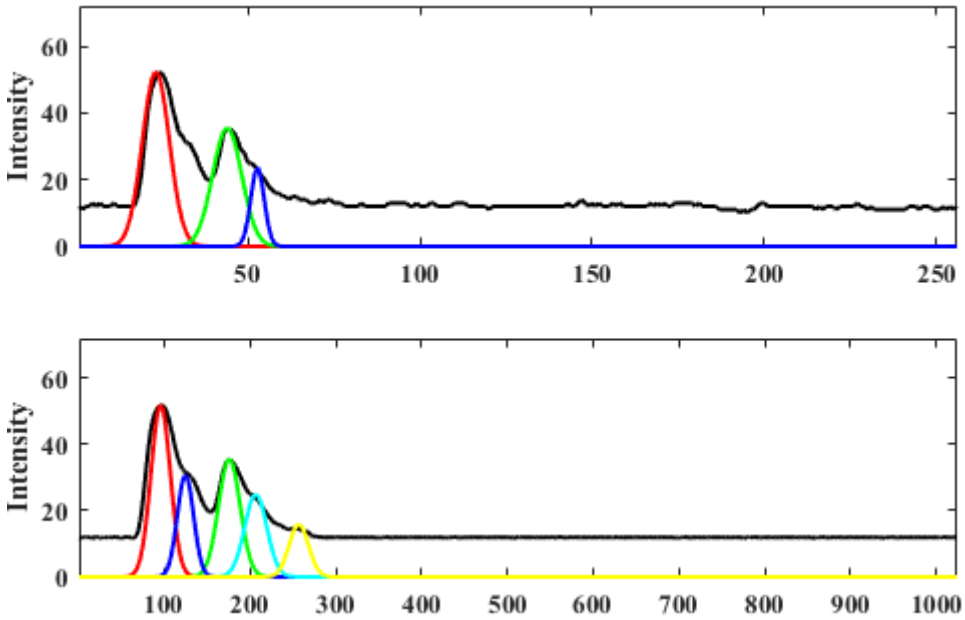

Figure. 2. Raw signal (256 data points) and output signal (1024 data points)

4.Conclusion

In this work, a CNN based full-waveform LiDAR super-resolution algorithm is studied. Without extra hardware and system measurements, a factor of 4 ranging resolution improvement is demonstrated using the algorithm with a Neon database. The novel CNN-based algorithm breaks the limitation caused by system equipment and complicated environment to get high resolution full-waveform LiDAR data. We also expect the improved resolution will be helpful for follow-up works such as waveform decomposition and classification.

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