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Photonic Blind Source Separation Based on Point cloud Analysis and Deep Learning

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Abstract: We proposed and demonstrated a blind source separation method utilizing deep learning-based point cloud analysis algorithms. By treating the signals as point clouds and utilizing their statistical information, signal of interest can be recovered.
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1. Introduction

Blind Source Separation (BSS) has long been a topic of interest in the field of telecommunication. In common multi-input, multi-output (MIMO) models, the signals received at the receiver can be considered a linear combination of signals from various transmission sources. The signal set at the receiver is the product of the signal set at the transmitter multiplied by a mixing matrix [1]. By recording the signal set at the receiver, it is possible to calculate the mixing matrix and then trace the original signals, thereby attaining the objective of interference management. Photonic BSS [2] is an analog signal-based method for blind source separation that resolves the mixing matrix by exclusively computing the statistical information of the received signals. Due to its reliance on statistical calculations, Photonic BSS requires less computational workload to calculate the mixture matrix. This implies that blind source separation can be performed regardless of workload sampling.

In the current era in which deep learning is gathering popularity, numerous researchers have attempted to solve blind source separation using deep learning techniques. The majority of these methods employ traditional BSS algorithms, which compute the received signal set as a sequence of continuous-time signals. On the other hand, Photonic BSS places a greater emphasis on the statistical information of the received signals, especially their distribution. This perspective enables Photonic BSS to benefit from treating the signals' distribution as two-dimensional or three-dimensional point clouds as opposed to continuous-time signals. Consequently, it becomes advantageous to leverage well-known and efficient network architectures designed for three-dimensional point cloud recognition, such as PointNet [3], when solving the BSS problem within the Photonic BSS framework.

In this paper, we propose and demonstrate a method for blind source separation that employs deep learning-based point cloud classification algorithms. We take advantage of the fact that many point cloud classification algorithms do not require significant amounts of data for model generation and can provide accurate classification results even with sampled input data. Regardless of a smaller quantity of data, Photonic BSS does not experience a significant impact on the statistical information of the data; rather, computational speed is increased. Therefore, this method is ideally suited for Photonic BSS computations, as it utilizes the under-sampling properties [4] of Photonic BSS for wideband RF signal processing.

2. System Setup

Our primary objective is to create a new point cloud dataset for training a neural network. This dataset contains point clouds with signals of three different modulation types. Included in these modulation types are pseudorandom binary sequence (PRBS), 16 quadrature amplitude modulation (16QAM), and Gaussian noise. These three distinct modulation types can be combined to create various 3D point clouds. The dataset also produces a 3x3 transformation matrix to represent the point cloud's mixing with signals. Fig. 1. (a) shows a point cloud composed of two PRBS signals, one of which is considered a signal of interest (SOI), and a 16QAM signal.

This dataset will then be used to train a neural network designed to conduct 3D point cloud transformation and classification. Fig. 1. (b) shows the architecture of the neural network. It contains several shared multi-layer perceptrons (MLP), which allow each point in the point cloud to undergo the same processing steps, enabling the network to learn shared representations and capture local patterns or structures present in the data. The output of the shared MLP for each point will then be fed into further layers or aggregation functions to acquire a global feature vector of fixed length representing the entire point cloud. The shared MLP ensures that the network can manage unordered and unstructured point cloud data, leveraging shared processing to learn meaningful representations from the individual points. The output of the network is a 3x3 de-mixing matrix, which can be used for blind source separation. This network model was trained using a dataset consisting of 15,000 point clouds with three modulation types of signals and 1,500 points per signal for 500 epochs. The network was trained in a Google Colab environment with an A100 GPU using a learning rate of 0.01. The duration of training was approximately three hours.

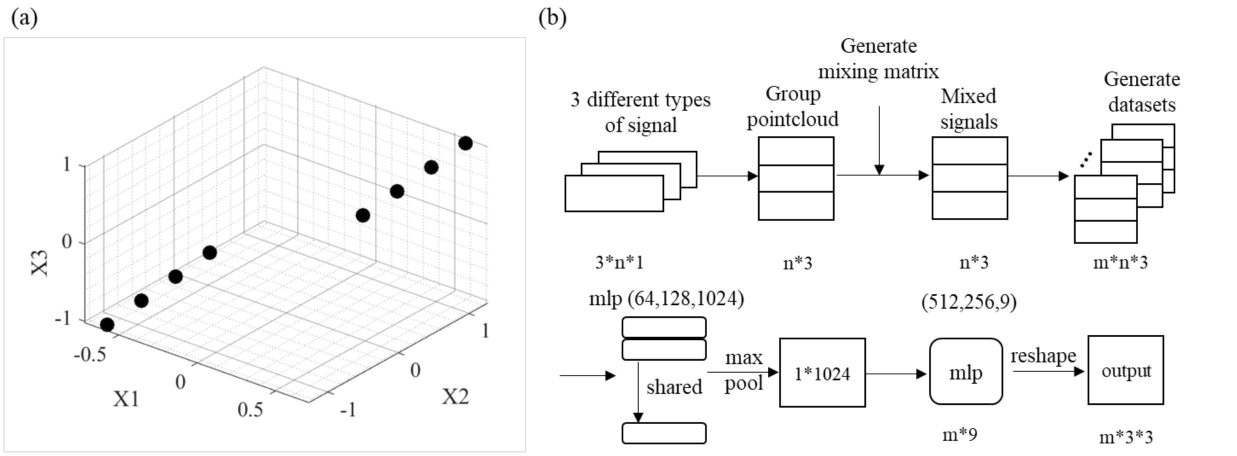

Fig. 1. (a) Point cloud of mixed signal. Types of signals used here are x1: PRBS (SOI), x2: PRBS and x3: 16QAM (b) System setup and network architecture.

3. Results and Analysis

The results are shown in Fig. 2. We use the mean square error to evaluate the loss. After 500 epochs, the average test loss of the model is around 33. Fig. 2. (a) shows a good example of difference of original time-domain signal of interest and the recovered SOI. The red curve shows the origin SOI, and the black curve indicates the recovered SOI after training model. This reveals that SOI (PRBS1) is separate from interference (QAM16 and PRBS2). Fig. 2. (b) indicates the variations between the mixed signal of channel one and the original SOI. The signal of interest is significantly changed by multiplying a mixing matrix. After training, the SOI can be recovered with precision.

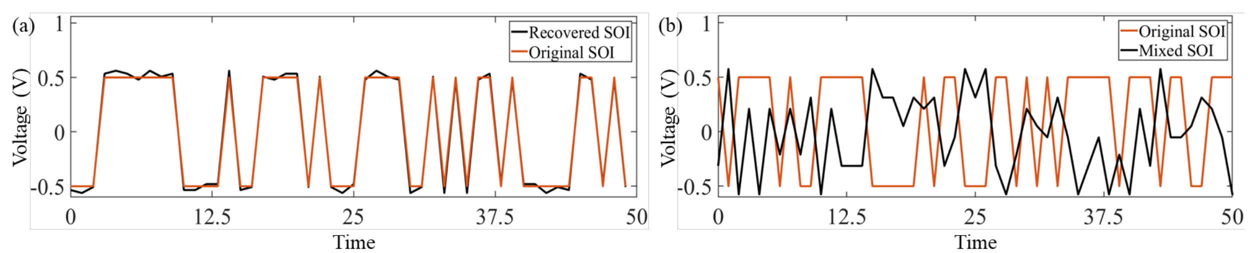

Fig. 2. (a) Comparison of recovered SOI and original SOI, red curve: original SOI, black curve: recovered SOI. (b) Comparison of mixed SOI and original SOI, red curve: original SOI, black curve: mixed SOI.

4. Conclusion

We proposed and demonstrated a method for blind source separation using point cloud analysis algorithms based on deep learning. It takes advantage of the point cloud-enabled deep learning method, treats input signals as point clouds rather than time sequences, and calculates their statistical information to solve blind source separation problems. This method is more suited to Photonic BSS and can reduce computational workload while processing wideband RF signals efficiently. After training on signal data point clouds, the network effectively separates the signal of interest. This work is supported by NSF grant number ECCS-2128608 and NJHF grant number PC 45-23.

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