IncepSeqNet : Advancing Signal Classification with Multi-Shape Augmentation (Student Abstract)

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Abstract

This work proposes and analyzes IncepSeqNet which is a new model combining the Inception Module with the innovative Multi-Shape Augmentation technique. IncepSeqNet excels in feature extraction from sequence signal data consisting of a number of complex numbers to achieve superior classification accuracy across various SNR(Signal-to-Noise Ratio) environments. Experimental results demonstrate IncepSeqNet's outperformance of existing models, particularly at low SNR levels. Furthermore, we have confirmed its applicability in practical 5G systems by using real-world signal data.

Introduction

The simultaneous advancement of machine learning technologies has been leading to the convergence of multidisciplinary industry fields. The fifth-generation mobile communication technology, which is rapidly evolving as an innovative communication technology to offer high-speed data transmission and low latency, can be one candidate. However, it is worth noting that conventional CNN(Convolutional Neural Network)-based models and the related techniques have been specialized primarily for handling image data in many cases. Our hands-on experience has experimentally demonstrated that the conventional augmentation techniques that have been used for images are not suitable for sequence signal data used in mobile networks. This research proposes the IncepSeqNet model, which is based on the Inception Module and incorporates a novel multi-shape augmentation technique for handling real-field 5G systems. This model aims to overcome the incongruity of traditional CNN models against the sequence signal data and extends its applicability. Additionally, by utilizing the signal dataset measured with practical commercial mobile base stations, this research contributes to bridging the gap between the recent mobile network technology and deep learning, demonstrating its potential applicability in the real-world.

IncepSeqNet

Multi-Shape Augmentation. The signal data we used belongs to a type of Zadoff-Chu sequence, possessing orthogonal characteristics. Each sequence is represented by sample data consisting of 144 complex numbers, comprising In-phase and Quadrature-phase components. We perform imagification technique to format Zadoff-chu sequence data in a manner similar to images. However, when we applied conventional image augmentation techniques to the imagified sequence data, we observed a significant performance degradation, as it differs from the characteristics of typical image data. Multi-Shape Augmentation assists in transforming imagification data into various forms, thereby enabling the extraction of more features through convolution operations among different elements. Figure 1 represents the framework of IncepSeqNet. In the Imagification Layer, complex number-based sequence signals are imagified and then subjected to multi-shape augmentation. The multi-shape along with the basic imagification shapes follows Equation 1.

$$R_i = \begin{cases} (H_{in},\ W_{in},\ 2), & \text{if } H_{in}, W_{in} \in \mathbb{Z} \\ (1,\ S,\ 2), & \text{otherwise} \end{cases} \tag{1}$$

R_i represents the format after the application of multi-shapes, with i taking on values from $i \in \{0, 1, 2, 3, 4\}$, resulting in the composition of five different inputs. S represents the number of complex elements constituting a single sequence data, and S follows the $H_{in} \times W_{in}$ format. When both H_{in} and W_{in} are integers, it allows for stacking and processing of In-phase and Quadrature-phase of signal data together, enabling efficient joint operations. In this research, the H_{in} and W_{in} values of the original input R_0 are set to be the same, resulting in a square format.

Inception Module. IncepSeqNet is configured to extract more feature maps through Inception Modules. Data processed through Multi-shapes augmentation undergo convolution operations with different filter sizes. The R_i resulting from Multi-Shape processing corresponds to convolution layers $C_{i\times 2}$ and $C_{i\times 2+1}$, which can be adaptively adjusted with different filter sizes. Features extracted through filters from each layer are then restructured into a single feature vector through flatten and concatenate operation processes. Subsequently, a simply structured fully connected layer is employed for index classification, making it suitable for inclusion in the work.

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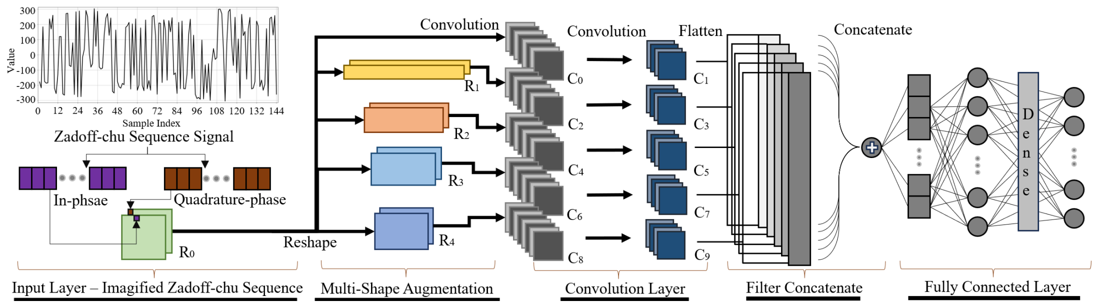

Figure 1: Framework of IncepSeqNet

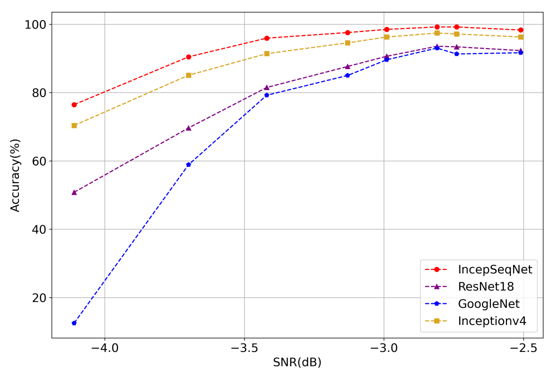

Figure 2: Performance of Various CNN Models and IncepSeqNet on DMRS Index Classification Accuracy

Experiments

Experimental Setup. For our experiments, we utilized DMRS (DeModulation Reference Signal) sequence signals (Han, Jo, and Kim 2022), which are composed of Zadoff-Chu sequences, with eight different indices. All data used in the experiments are measured and collected in a real 5G system environment. The signals were extracted in eight different SNR(Signal to Noise) levels, and models were trained individually for each SNR level. To validate the performance of IncepSeqNet, we conducted index classification of the sequence data by using the existing CNN models, namely ResNet18 (He et al. 2016), GoogleNet (Szegedy et al. 2015) with Inception modules, and InceptionV4 (Szegedy et al. 2017). The filter sizes $C_{i\times 2}$ and $C_{i\times 2+1}$ were adaptively employed with both 2×2 and 3×3 filters based on the shape of R_i. Then the conventional models are compared with our proposed model.

Experimental Results. Figure 2 shows the index classification performance results of IncepSeqNet. As evident from the graph, IncepSeqNet exhibited better classification accuracy across all eight SNR levels compared to other existing models. In particular, it showed an improvement of 5%p compared to the more advanced InceptionV4 model at the lowest SNR of -4.11dB. This demonstrates the performance enhancement achieved by IncepSeqNet with the addition of multi-shape augmentation.

Additionally, Table 1 presents the average training time for each model. IncepSeqNet improved training time by approximately 1.3 to 3.87 times compared to the existing models while confirming its applicability in real systems.

	GoogleNet	ResNet18	InceptionV4	**IncepSeqNet**
Time(s)	632.8	886.2	305.5	**228.9**

Table 1: Average Training Time per SNR by Model

Conclusion

In this work, we proposed IncepSeqNet, which incorporates a new multi-shape augmentation technique into the existing inception module. We conducted experiments using real collected signal data to verify its applicability. We also compared the signal classification accuracy and training time of the proposed model with existing deep learning models. In future research, we plan to further develop the model to extract a wider range of features while making it more lightweight.

Acknowledgements

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