Research Paper Presentation

A Data Preprocessing Method for Automatic Modulation Classification Based on CNN

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Abbrevations

1. Convolutional neural networks = CNNs
2. Automatic modulation classification = AMC
3. likelihood-based = LB
4. feature-based = FB
5. convolutional long short-term deep neural network = CLDNN
6. long short-term memory = LSTM
7. deep residual network = ResNet
8. data preprocessing method = DPM

Abstract

- A novel data preprocessing method is proposed to markedly improve CNN-based automatic modulation classification.
- The experimental results show that using the proposed method gains approximately 10% accuracy improvement in a simple CNN.
- According to the form of the preprocessed data, we designed a CNN with residual blocks to reach a maximum accuracy of 93.7% when the signal-to-noise ratio is 14 dB, which outperforms state-of-the-art automatic modulation classifiers.

Definitions

Residual Block

Residual blocks are basically a special case of highway networks without any gates in their skip connections. They allows the flow of memory(or information) from initial layers to the last layers.

CNN

Convolutional Neural Network is a class of deep neural networks, most commonly applied to analyzing visual imagery.

Introduction

- Automatic modulation classification (AMC) is a technology used to classify the modulation scheme of an unknown recieved signal.
- AMC is crucial technology is used in various civilian and military communication applications.
- Algorithms to solve AMC problems can be divided into two categories
  - Likelihood Based(LB)
  - Feature Based(FB)

- From Bayes decision theory, the LB algorithms often an optimal solution to maximise probability of correct classification but LB approach suffers from unacceptably high computational complexity.
- FB approach is much easier to implement and based on features extracted from recieved signal.
- The recieved signal is sent to CNN where the recieved signal's modulations are classified.
- In this paper, we'll focus majorly on two aspects
  - A proposed DPM, a data preprocessing method.
  - Specially designed a CNN with residual blocks based on form of preprocessed data.

Signal model and the proposed DPM

The recieved signal can be expressed as

$$y(t) = h(t) * x(t) + n(t) \tag{1}$$

where,

- n(t) = Channel Interference
- h(t) = Channel Impulse Response
- * = Convolution Operator
- x(t) = Modulated Signal
- y(t) = Recieved Signal

The signal sample space Y_{dts} is generated from a discrete time sampling of y(t) and can be expressed as

$$Y_{dts} = [S_1, S_2, S_3, ..., S_l, ...S_L], 1 \leq l \leq L \tag{2}$$

L = number of sample points
$S_l = l^{th}$ sample point of Y_{dts}

$$S_l = [I_l Q_l]^T \tag{3}$$

I_l, Q_l are real and imaginary values of samples point S_l.

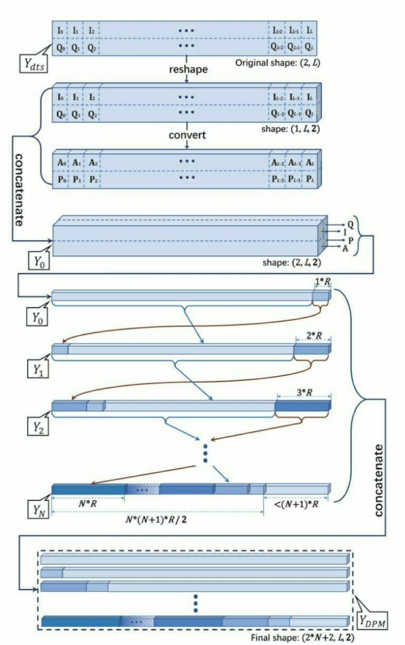
The Proposed DPM

Hypothesize that x(t) is digital modulation signal Y_{dts} comprises M symbols $\{y_m\}_{m=1}^{M}$ and each symbol y_m consists of B sample points $\{S_{mb}\}_{m=1}^{B}$ (MXB=L).

- We assume features of modulation scheme exists in the differences between signal symbols and CNN classifiers achieve the modulation classification by comparing the values of each B sample point in the M signal symbols

ALGOITHM OF THE PROPOSED DPM

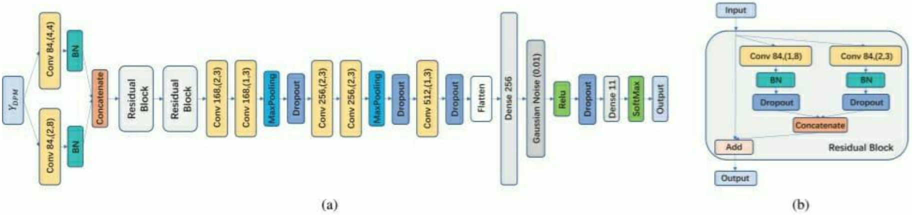
DPM Algorithm	
1.	Reshape Y_{dts} to size $1 \times L \times 2$, and each $1 \times 1 \times 2$ unit represents a sample point.
2.	Calculate the amplitude value $A_l = \sqrt{{I_l}^2 + {Q_l}^2}$ and the phase value $P_l = \tan^{-1}(\frac{I_l}{Q_l})$ of each sample point s_l.
3.	Concatenate each $[A_l, P_l]$ and s_l to generate Y_0 with size $2 \times L \times 2$, and each $2 \times 1 \times 2$ unit represents a sample matrix $\begin{bmatrix} I_l & Q_l \\ A_l & P_l \end{bmatrix}$.
4.	Set a positive integer R; set $n = 0$.
5.	$ns = n * (n+1) * R/2$; implement a length-ns circular right shift on Y_0 in the second dimension to get Y_n.
6.	$n = (n+1)$.
7.	If $n * (n+1) * R/2 < L$: back to 5. Else: $NS = ns, N = n$.
8.	Concatenate $\{Y_n\}_{n=0}^{N}$ to get Y_{DPM} with size $(2 * N + 2) \times L \times 2$ as the input of CNN.



Y_{dts}
Original shape: (2, L)
reshape
shape: (1, L, 2)
convert
concatenate
Y_0
shape: (2, L, 2)
Q
I
P
A
1*R
2*R
3*R
Y_1
Y_2
Y_N
N*R
<(N+1)*R
N*(N+1)*R / 2
concatenate
Y_{DPM}
Final shape: (2*N+2, L, 2)

Structure of networks

In this paper, we propose a specially designed CNN(SCNN) with residual blocks to identify the modulation scheme of DPM- processed signal dataset.

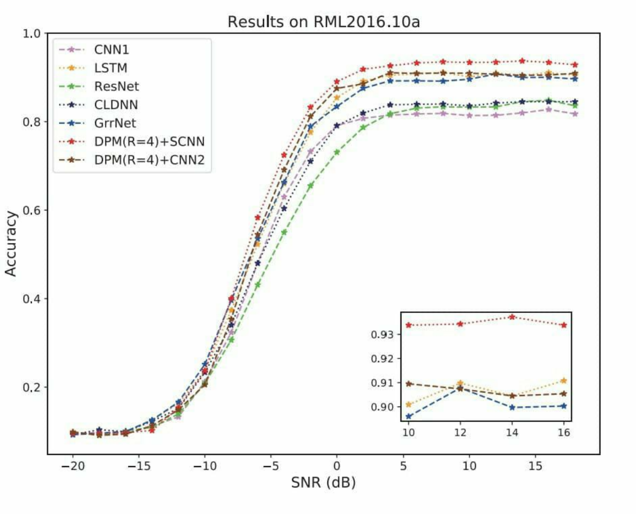


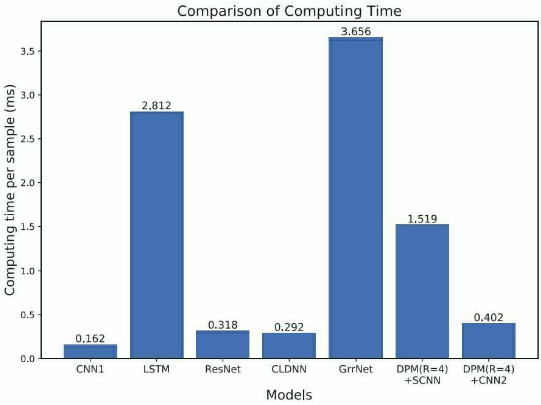
- The drop out rate of dropout layers is 0.5 and pool size of the pooling layer is 2×2.
- All the convolutional layers use a rectified linear unit as the activation function.
- A gaussian noise layer is adopted to reduce the overfitting.

The special designs in this network

- Each $2 \times 1 \times 2$ unit in $\{Y_n\}_{n=0}^{N}$ is a sample point.
- The first two convolutional layers are parallel to each other. To focus on extracting the horizontal and vertical features, the fillers of these pairs of convolutional layers are set with a narrow shape and a comparably wide and short shape respectively.

Experimental Results




Comparison of Computing Time
Computing time per sample (ms)
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.162
2.812
0.318
0.292
3.656
1.519
0.402
CNN1
LSTM
ResNet
CLDNN
GrrNet
DPM(R=4) +SCNN
DPM(R=4) +CNN2
Models

Overall AveAcc of the Four Models on MD2020

	CNN1	LSTM	SCNN	CNN2
Version I	44.75%	42.63%	**60.06%**	55.55%
Version II	43.85%	42.61%	**58.24%**	54.11%
Version III	43.74%	40.17%	**58.04%**	54.49%
Version IV	43.76%	39.18%	**57.00%**	54.39%