UC San Diego
JACOBS SCHOOL OF ENGINEERING

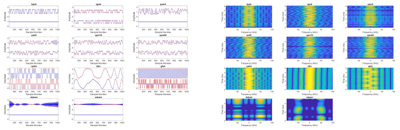
Classifying the Modulation Type of a Wireless Signal

SCRIPPS INSTITUTION OF OCEANOGRAPHY

Team 42: Venkatesh Sathyanarayanan, Rui Shang, Richard Bell, Jahya Burke
Department of Electrical and Computer Engineering, University of California San Diego, La Jolla, CA, 92092, USA

Introduction

- Modulation classification: For a given set of digitized electromagnetic (EM) samples, we classify what modulation data the EM wave contains.
- Previous works use expert features to classify



- Deep neural networks learn the best features from the data without expert knowledge
- A Convolutional Neural Network (CNN) and residual NN (RESNET) are considered.
- The input is 5ms of sampled IQ data and the output is one of the eleven modulation types.
- We have also explored the effect of frequency error on the performance

Dataset

The dataset used is generated synthetic signals with introduced channel impairments.

Number of Samples: 10k per class (11 classes)
Sample Size : 2x1024
- 2 rows representing the I and Q of the IQ.

Sampling Frequency: 20KHz
- 5ms IQ samples containing 128 symbols

Labels: One hot encoding of modulation type

The sampling duration and the samples per symbol length is reasonable for a stationary channel assumption and modulation types used.

CNN

Methods

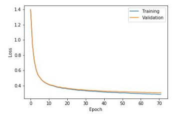
Network Architecture:
Input→ ConvBlock(6x) → FC+Softmax → Output

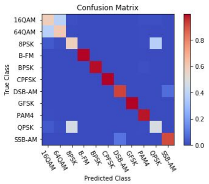
Dataset: 100k Synthetic Signals
70k Train, 20k Test, 10k Val
MiniBatch Gradient Descent:
Learn Rate - 0.00001
Batch Size - 32

ConvBlock
- Convolution k=8
- Batch Normalization
- Max Pooling
- Activation

Results

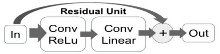
Test Accuracy = 82%





ResNet

Methods



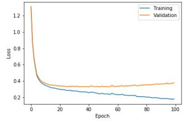
Network Architecture:
Input→ ResBlock(6x) → FC(3x) → Output

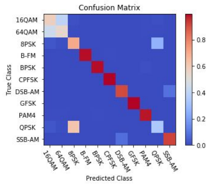
Dataset: 100k Synthetic Signals
70k Train, 20k Test, 10k Val
MiniBatch Gradient Descent:
Learn Rate - 0.00001
Batch Size - 32

ResBlock
- Convolution k=1
- Residual Unit
- Residual Unit
- Max Pooling

Results

Test Accuracy = 81%

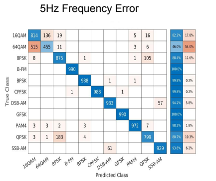


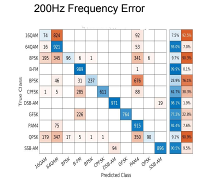


Frequency errors

Methods

- Center frequency of a signal is typically off due to the effect of clock source inaccuracy and doppler.
- This causes a phase error that is ramping with time and from a constellation diagram point of view, frequency errors (Fe) cause the points to rotate with time.
- We generate test data with Fe = 200 Hz and study how our model trained on 5Hz Fe classifies 200Hz Fe data.





Discussion

Model Performance: The basic CNN implementation outperformed ResNet by a small margin of 1% in test accuracy. The ResNet loss shows the model overfitting. So more Data is likely needed to trai

Accuracy	CNN	Resnet
Train	84%	92%
Test	82%	81%

Performance effects due to frequency errors
- For Fe=200hz, the points rotate by 360 degrees in 5 ms.
- In 5ms the points are spread all over the constellation diagram and therefore many of the phase modulation types which are sensitive to frequency errors, are confused as 64 QAM.

Why Deep NN Outperform Traditional Models
We understand physics behind the problem accurately. Still, modulation classification is quite a challenge. In the illustration below [5] - note the complexity of the equation involved - thanks to the ability of deep neural networks to understand complex relationships that it is able to outperform traditional models.

Given sampled r(t), our model is attempting to estimate what the "i" is in $s_k^{(i)}$

$$r(t) = s(t; \boldsymbol{u}_i) + n(t)$$

r - Received signal
n - Additive noise

where $$s(t; \boldsymbol{u}_i) = a_i e^{j2\pi\Delta f t} e^{j\theta} \sum_{k=1}^{K} e^{j\phi_k} \boxed{s_k^{(i)}} g(t-(k-1)T-\varepsilon T),$$

$$a_i = \sqrt{(E_s/\sigma^2_{s^{(i)}}\ E_p)},$$

$$g(t) = p_{TX}(t) \otimes h(t)$$

$$h(t) = \sum_{p=1}^{P} \alpha_p\, e^{j\varphi_p} \delta(t-\tau_p$$

$\alpha_p\ \varphi_p\ \tau_p$ Magnitude, phase and delay of each multipath

Es - Baseband signal Energy
Ep - Pulse energy
Ptx - Tranmit pulse shape
h - channle impulse response with P multipaths
$s_k^{(i)}$ data symbol from ith modulation format
ϕ_k - phase jitter of the kth symbol
ε - sampling time error
K - symbol period
u - set of unknowns

Future

- Adapt alternate architectures → VGGnet, LSTM.
- Utilize real world dataset from DEEPSIG.io
- Focus on subset of classes to attempt performance improvement.
- Effect of frame misalignment on performance

References

1. O. A. Dobre, A. Abdi, Y. Bar-Ness and W. Su, "Survey of automatic modulation classification techniques: classical approaches and new trends," in IET Communications, vol. 1, no. 2, pp. 137-156, April 2007.
2. T. J. O'Shea, T. Roy and T. C. Clancy, "Over-the-Air Deep Learning Based Radio Signal Classification," in IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 168-179, Feb. 2018. doi:10.1109/JSTSP.2018.2797022
3. T. O'Shea and J. Hoydis, "An Introduction to Deep Learning for the Physical Layer," in IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 4, pp. 563-575, Dec. 2017. doi: 10.1109/TCCN.2017.2758370
4. Modulation classification MATLAB: https://www.mathworks.com/help/deeplearning/examples/modulation-classification-with-deep-learning.html
5. O. A. Dobre, A. Abdi, Y. Bar-Ness and W. Su, "Survey of automatic modulation classification techniques: classical approaches and new trends," in *IET Communications*, vol. 1, no. 2, pp. 137-156, April 2007. doi: 10.1049/iet-com:20050176