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MODEL-BASED ASSISTED DEEP LEARNING FOR ADAPTIVE, RESILIENT TARGET TRACKING AND IDENTIFICATION OF ELECTROMAGNETIC INTERFERENCE (EMI)

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14. ABSTRACT
This report summarizes the preliminary research effort on target tracking and identification of spoofing and jamming attacks on satellites from an Electromagnetic Interference (EMI) source. We hypothesize that it is possible to identify and track both active and passive EMI sources using the Radio Frequency (RF) signatures of different sources. The RF signatures are input into to a model-based deep neural network (DNN) that classifies and tracks different objects. To test our hypothesis, we study two settings: a) QAM modulation classification using a 2D convolutional neural network and b) people counting system using a MIMO radar with a 3D convolutional neural network.

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1. SUMMARY

This report summarizes our research effort on model-based adaptive target tracking and identification of spoofing and jamming attacks on satellites from an Electromagnetic Interference (EMI) source. We hypothesize that it is possible to identify and track both active and passive EMI sources using the Radio Frequency (RF) signatures of different sources. The RF signatures are input into to a model-based deep neural network (DNN) that classifies and tracks different objects.

Our preliminary results indicate that for active EMI sources, i.e., the sources that emit RF signals using different modulation schemes, the identification accuracy of the RF modulation schemes of an EMI source using a DNN depends greatly of the quality of the RF signatures which in turn, is the function of the channels. In particular, if the channel is line-of-sight and the signal-to-noise ratio (SNR) is large, then the classification of modulation types is highly accurate (> 95%). On the other hand, if the channel parameters are unknown and/or fluctuated, and the SNR is low, then the classification accuracy is low (< 60%). The performance of modulation type identification led us to conclude that object tracking based on modulation types in real-world settings will be very difficult. As such, a major effort on this research is focused on classifying passive sources using active radars using people counting system as a prototype.

Instead of using simulations, we built a small-scale test environment in our laboratory to test the hypothesis. Our proposed people counting system uses multiple transmit antennas to scan the environment by sending out mmWave radar chirps. Signals bounced back from objects are received by multiple receive antennas, processed, and store into digital database. We then perform feature extraction on the digital data and feed the features into a convolution neural network to perform object classification and tracking. In these experiments, we consider walking people as moving objects. Our initial result show that in limited settings, e.g., the lab environment, a convolutional neural network can accurately identify different objects (> 95 %) using the RF signatures.

2. INTRODUCTION

Object identification and tracking have been well studied in many scientific and engineering disciplines [1][2][3][4][5]. They are the underlying components in many technologies ranging from global positioning systems (GPS) for early detection and tracking missiles in flight [6][7][8] enabling self-driving cars [9]. In addition, future wireless communication systems use massive Multiple Input Multiple Output (MIMO) beamforming [10] and Free-Space-Optical (FSO) communication technologies [11][12][13] that enable a sender to transmit data by focusing its RF beam or laser beam directly on a receiver. These focused transmissions increase signal-to-noise ratio (SNR), reduces required transmit power as well as multi-user interference. However, the focused transmissions rely critically on the ability to accurately track and identify a receiver's locations.

Traditionally, object tracking and identification technologies were model-based driven due to its mathematical elegance and efficiency, and perhaps more importantly, due to the lack of training data. The model-based approach incorporates prior knowledge about a problem based on either physical laws or well-established intuitions via mathematical models to capture the object dynamics and properties for accurate tracking and classification. For this reason, model-based approach is highly efficient in many settings that can be accurately modeled through a few parameters. An exemplary example of the model-based approach is the Kalman filter [14][15][16]. Kalman filter has been used successfully in many applications, notably in tracking a target subject to noisy observations. The key to the success of Kalman filter in tracking is the combination of the accurate mathematical model for the target's dynamics (e.g., velocity, acceleration, etc) and the empirical real-time noisy measurements of these values. Kalman filter estimates the model parameters efficiently (fast) via a set of recursive equations that update the values of parameters based on incremental measurements/observations and the assumed mathematical model dynamics.

A major drawback of Kalman filter for tracking is that its performance depends heavily on the supposedly accurate mathematical model based on some reasonable assumptions such as physical laws or experience. However, if the mathematical model is not rich enough to capture all minute details of the considered setting, then the best performance of a Kalman filter will be limited by the family of mathematical models under consideration.

To that end, this research investigated deep neural networks (DNN) for identifying and tracking objects. DNN is a class of machine learning methods based on artificial neural networks (ANNs) that has been shown to perform exceptionally well in many real-world scenarios. DNN architecture allows the model to learn complex dynamics and features from a large database that would be difficult to model mathematically.

3. METHODS, ASSUMPTIONS, AND PROCEDURES

This section will describe two separate efforts. The first effort is on detecting the RF modulation types of an EMI source using different types of convolution neural networks (CNNs). The study is done entirely in Matlab simulation environment. The second effort is on detecting number of people in a room and track them using their RF their signatures from an active radar system as inputs into a 3-D CNN. These types of systems are commonly known and people counting systems [17][18][19]. In contrast with the first effort, all the RF signature are not simulated. Rather, they are collected in real-time using a MIMO-based mmWave radar system. Next, we perform feature extraction on the raw data and feeds the features into a 3D convolution neural network to detect the number of people.

3.1 Active EMI Source-Passive Modulation Classification

Database Creation

We have continued to extended our previous on creating datasets for differentiation various RF modulation types. We created a synthetic dataset to allow the flexibility to tune the parameters for modeling different settings. In general, the use of synthetic datasets is discouraged since synthetic datasets often deviate from the actual real-world observations due to the imperfect knowledge and high degree of complexity to accurately model practical scenarios. However, in our cases, RF signals are not only understood, but also for the most part, synthetically generated. Based on this reason, we believe that appropriate synthetic datasets can be used effectively to train DNNs to be used in real-world scenarios. To that end, we used Matlab Communication ToolBox to create the dataset. The format of each dataset entry is shown in Fig. 1.

Modulation type	**SNR**	**Channel Type**	**Channel params**	**Data**
QAM-4	30dB	Rician	$(0.1, 0.2, \ldots, -2)$	$(0.1, -.9, -0.1, \ldots, 0.2)$

Figure 1. Format of an entry in the dataset. ***The label is in the first column and the features are in the remaining columns***

Currently, modulation type consists of 10 different QAM, ranging from QAM-2 to QAM-1024 with the number of constellations doubled for each type. SNR varies from 20dB to 50dB with the step size of 2, and is normalized. Channel type consists of 3 different categories: Rayleigh, Rician, and None. Channel parameters consists of the channel parameters corresponding to the channel types. These are used to capture multiple phenomenon such as channel fading and Doppler's effect. Data consists of 1024 samples.

CNN architecture

An important task in detecting and localizing an EMI is the ability to recognize its RF signature. As a first step, we implemented some preliminary DNN architectures for classifying different signal modulation type based on the received data. While we implemented many architectures, in this report we only describe a 4-level deep convolutional neural network (CNN) architecture and its performance. This CNN architecture is not chosen for its best performance. Rather, it shows typical performances of our current effort as we are still exploring on other architectures. We use PyTorch to implement the proposed CNNs. The CNN consists of 4 layers. Each input consisting of 1024 samples is fed into the first layer of the CNN which consists of one-dimensional convolution with 1 input channel, 16 output channels, kernel size of 3, stride of 1, and padding of 2. The outputs of the convolution operations are fed through a Rectified Linear Unit (ReLU). The output of ReLU is zero if the input is negative and equal to the input if the input is positive. One dimensional maxpooling with kernel size of 2 is then applied to the outputs of ReLU to reduce the dimension by 2. Fig. 2 shows the detail of the first convolutional layer in the CNN used in our experiments.

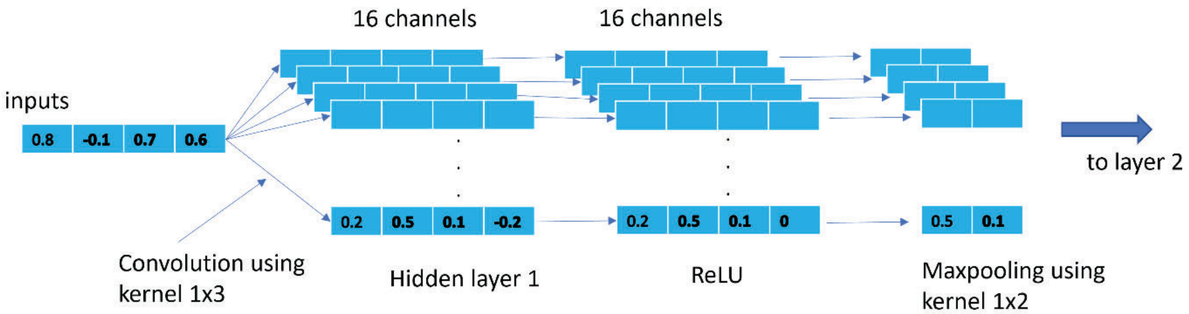

Figure 2. First layer of the proposed CNN. ***The structure of the remaining layers (not shown) are similar. The only differences are the sizes of input and output***

Similarly, all the remaining layers have identical structure to that of the first layer, but the number of input and output channels are different. The second layer has 16 input channels and 32 output channels. The third layer has 32 input channels and 64 output channels. The fourth layer has 64 input channels and 128 output channels. Other parameters are the same as those of first layer. The final output layer consists of a flatten layer connected to a softmax layer to predict the final outputs. We use cross entropy as the loss function during training and testing.

3.2 People Counting System Using mmWave MIMO Radar

The goal of this effort is to determine whether a mmWave MIMO radar can automatically detect various objects, specifically, count the number of people in the room by active scanning. While there exist many people counting systems, they are often video-based systems [20]-[22] that often acquire high-resolution sensor data. There are also systems that use RF data [23]-[29]. On the other hand, our research is focused on counting the number of people in the room using sparse mmWave MIMO data. Fig. 3 shows the set up for our experiment in a 6m x 10m room.

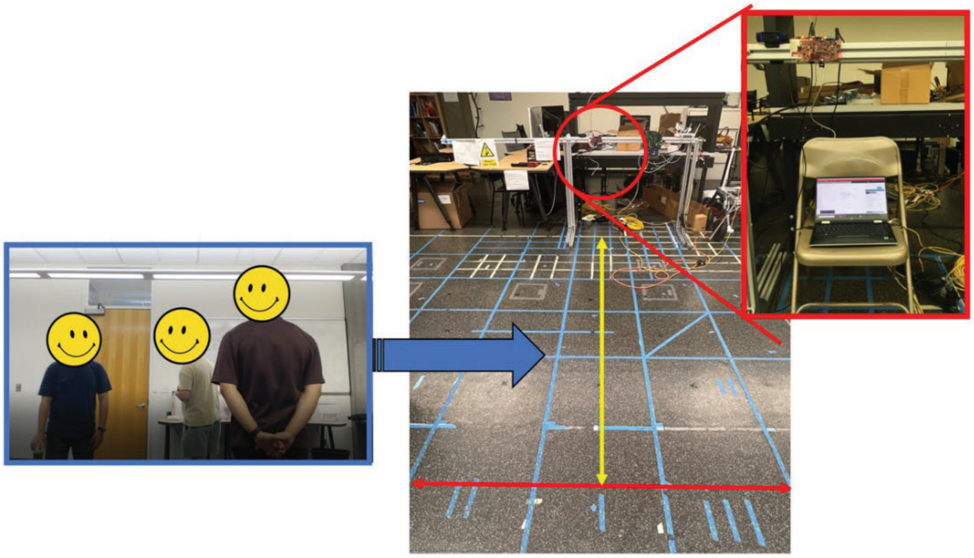

Figure 3. Experimental setup detecting the number of people in the room. ***People of different heights are walking in a confined space of 6m x 10m***

We use the IWR6843ISK MMWAVEICBOOST, a mmWave active radar from Texas Instruments to scan the room. There are 4 receive and 3 transmit onboard antennas. Each antenna has 120-degree azimuth field of view and 30-degree elevation field of view. Fig. 3 shows where the radar is mounted relative to where the people are walking. To control the experiment parameters, the floor is marked with tapes running along the vertical and horizontal directions. People are instructed to walk along these directions in addition to walk in random directions. We also have video cameras to record the video data of the experiments. Videos are not used in determining the number of people, rather they are used to verify the correctness data collection and post analysis.

Database Creation and Feature Extraction

To collect the training data, we employed a total of 12 different people of different heights ranging from 5’2” to 5’11, and genders in experiments. The collected data is divided into 4 groups: Group 0, Group 1, Group 2, and Group 3 with Group *n* contains *n* people walking in the room simultaneously. The number of hours of data for each group is shown in Table. 1

Table 1. Amount of data in hours collected for each group

Group 0	Group 1	Group 2	Group 3
2 hours	8.5 hours	8.5 hours	4.5 hours

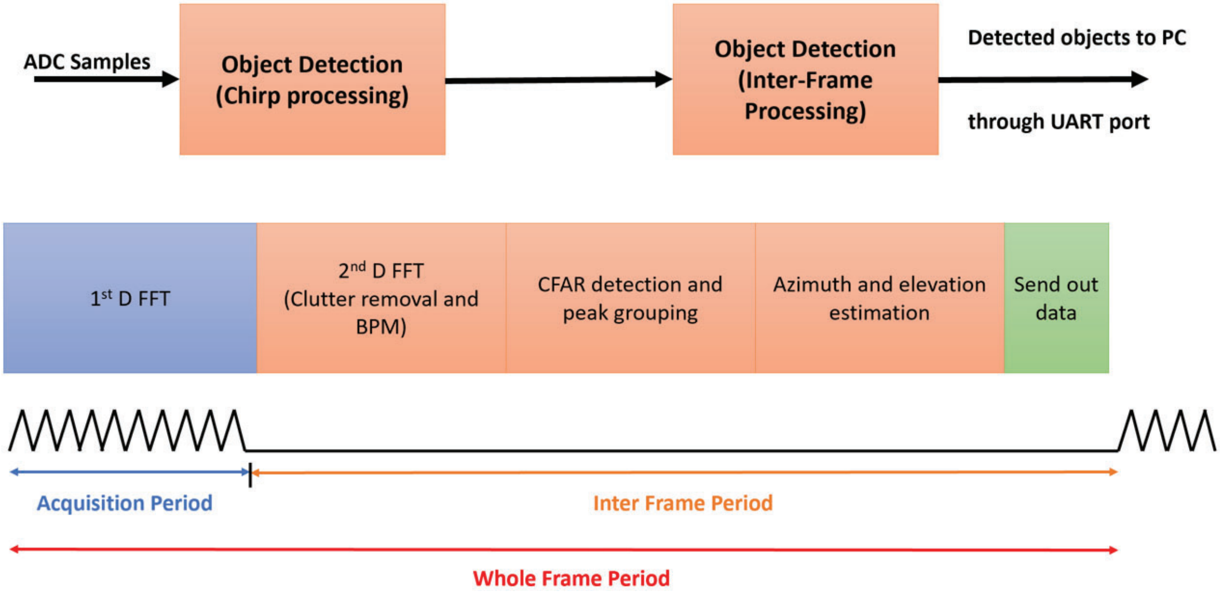

Figure 4. Extracting features from RF signals. ***Features/objects contain the number of identified objects, their Doppler velocities, their x,y,z positions and the relative SNR***

The steps for data acquisition and feature extraction are as follows. The IWR6843ISK MMWAVEICBOOST scans the room by sending out RF chirps, measures the reflected RF signals, processes into features (objects) and transferred to the PC as shown in Fig. 4. Specifically, the feature extraction (object detection) is accomplished in several steps. First, 1D range FFT is used on the data from receive antennas for every chirp that are connected with the chirping pattern on the transmit antennas during the chirp processing period. Next, 2D FFT, CFAR detection, peak grouping, and angle of arrival processing are performed. 2D FFT are meant to remove clutters. CFAR is a classical adaptive constant-false-alarm rate [30] to remove noise and interference. Peak grouping is used to detect the objects based on the relative SNR. The estimation of azimuth and elevation are used to determine the *x,y,z* positions of each object. Doppler velocity of an object, i.e., the relative velocity with the direction of the radar, is also estimated. These identified objects/features are sent to the PC in real-time for storage. Fig. 5 shows an example of detected features/objects. Data are collected and processed in frames at the rate of 10 frames per second.

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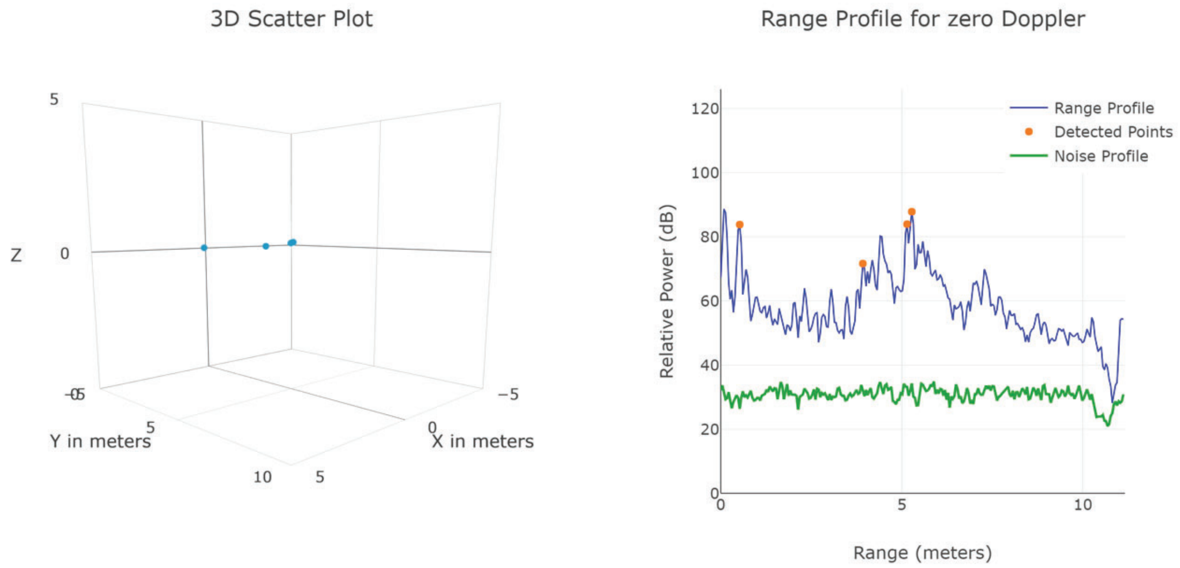


Figure 5. Positions of detected objects and their relative SNRs. ***The peak grouping algorithm identifies the important objects based on their relative SNRs***

3D Convolutional Neural Networks

The proposed 3D convolutional neural network for determining the number of the people in room is shown in Fig. 6. Each training example to the 3D CNN consists of 5 seconds worth of continuous 3D frames that consist of *x,y,z* positions, the Doppler velocities of the detected objects together with their labels (0,1, 2, or 3 people). For example, a 5-minute RF data segment is shaped into 60 continuous 3D frames. The size of each frame is 50x20x4, where 50 represents 5x10 seconds as a result of sampling data at 10 frames per second, 20 represents detected objects within each frame, and 4 represents coordinates and Doppler velocity information (*x,y,z,v*).

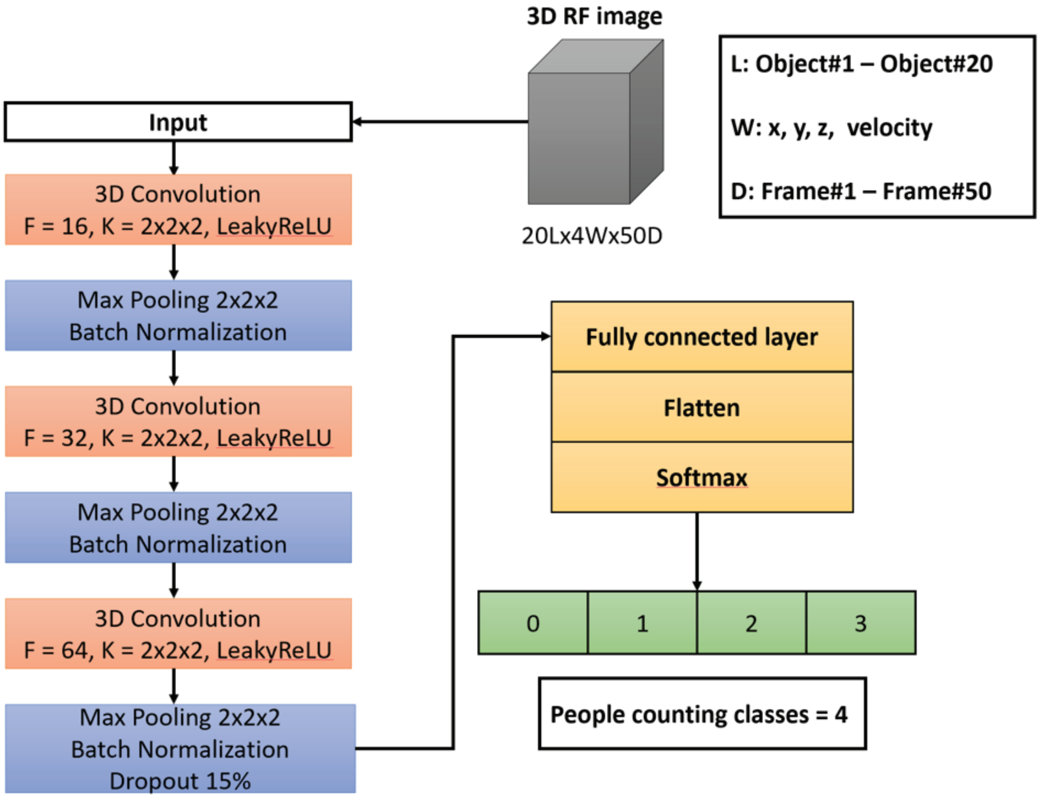


Figure 6. Architecture of the 3D convolutional neural networks. ***The inputs are a batch of 50 frames. Each frame consists of a number of objects with their positions and Doppler velocities***

4. RESULTS AND DISCUSSION

4.1 Active EMI Source-Passive Modulation Classification

In this section, we present the results of using the described CNN to classify different QAM modulations. We use Adam optimizer for CNN with the learning rate of 0.0001 and batch size of 128. The number of trainable parameters is 144,302. We use 80% of the dataset for training and 20% for testing. Fig. 7 shows that the proposed CNN can classify QAM modulations close to a 100% accuracy when the number of constellation points is 256 or fewer when SNR is greater than 20dB and channel is line-of-sight.

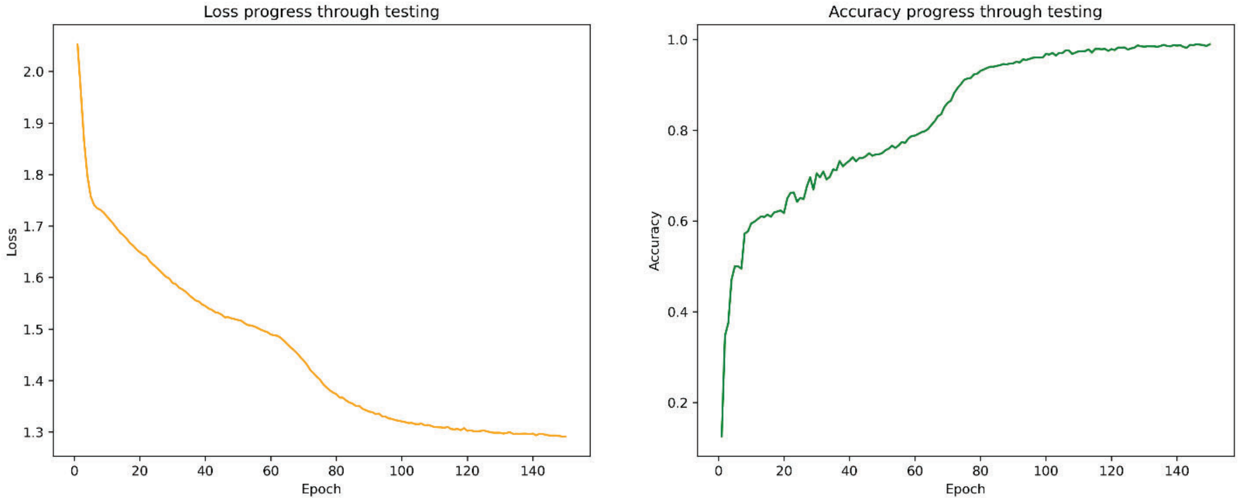


Figure 7. Test loss and accuracy as functions of epochs for classifying QAM-2 to QAM-256. ***The accuracy reaches 100%***

On the other hand, Fig. 8 shows that the accuracy decreases sharply to below 90% when the maximum number of constellation points increases to 512 with the SNR and channel parameters being kept the same as before.

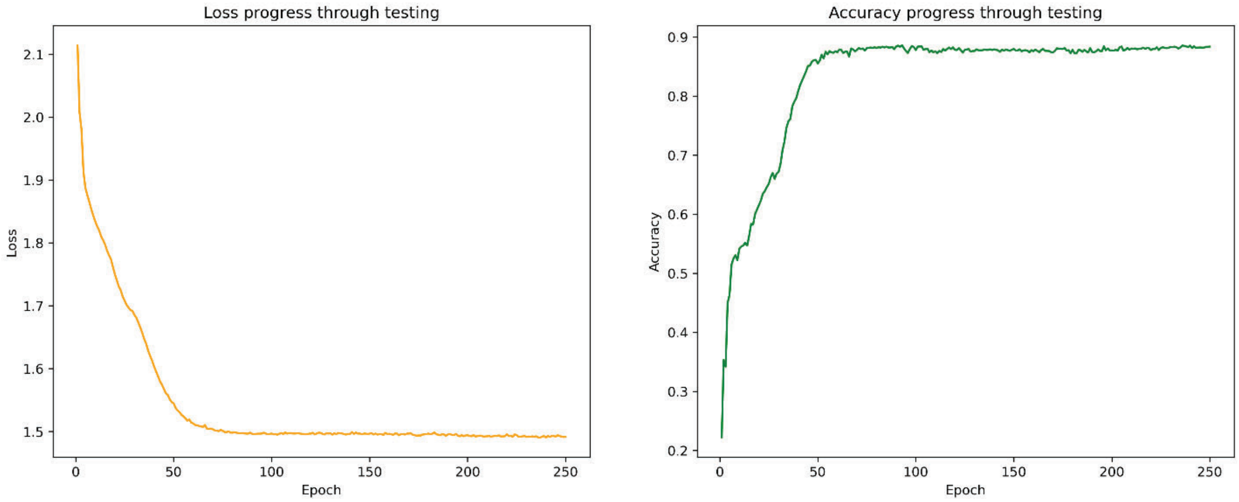


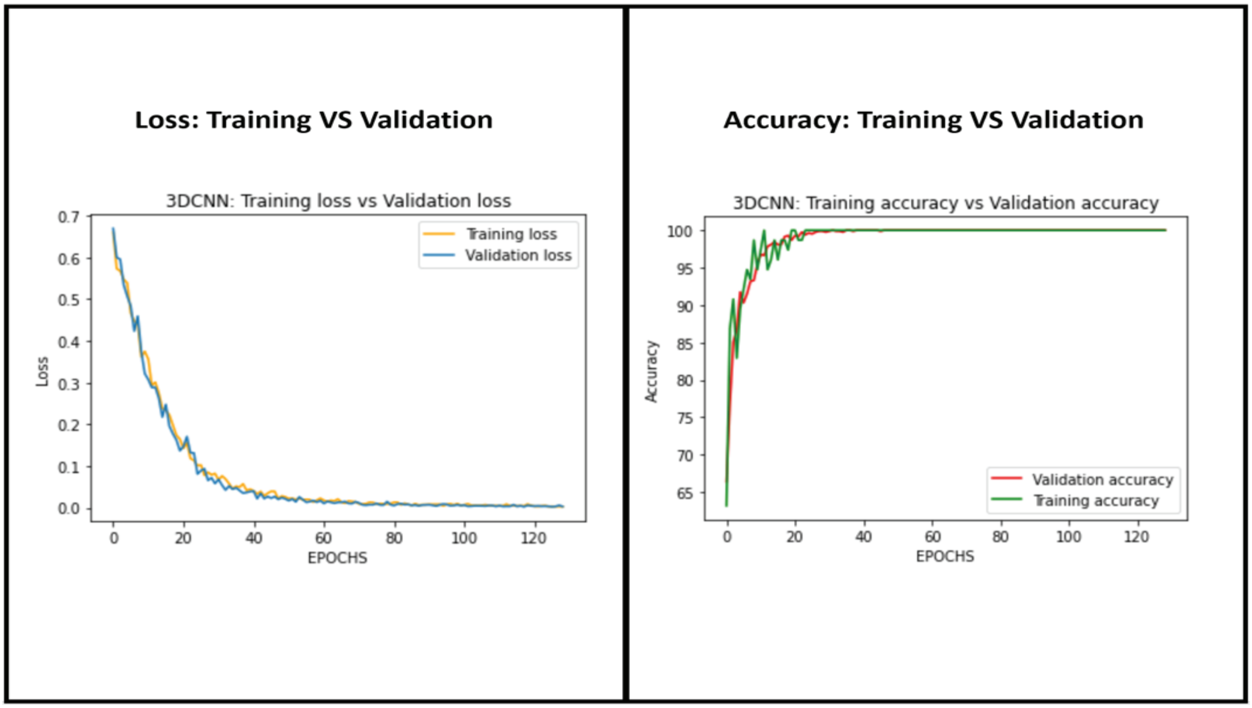
Figure 8. Test loss and accuracy as functions of epochs for classifying QAM-2 to QAM-512. ***The accuracy decreases to slightly below 90%***

In general, the current CNN cannot classify among the QAM modulations with the number of constellation points greater 1024. There are a couple reasons for this. The additive Gaussian noise is perhaps a bit too big as such for QAM modulation with large number of constellation points (> 1024), the codewords are not as distinctive. Second, since the input to the CNN is only 1024 samples, it is more difficult to learn to distinct the modulation type for QAM-1024 because QAM-1024 itself already consists of 1024 points.

With a typical parameters Raleigh fading channels, the performance of the proposed CNN can only reach an accuracy of 54% in classifying QAM-2 to QAM-32. Rician channels with one and two dominant paths performed slightly better at 62% accuracy in classifying QAM-2 to QAM-32.

4.2 People Counting System

In this section, we show the performance of the people counting system. We use 90% of the database is used for training while 10% is used for validation. The validation data consists of different individuals from those in the training data. We use Adam optimizer for CNN with the learning rate of 0.0001 and batch size of 128. Fig. 9 shows the loss vs. validation as function of number of epochs (training time) when system tries to detect whether there is a person present or not. As expected, the accuracy increases as training time increases. Furthermore, the validation accuracy reaches 100% only after 30 epochs.



Loss: Training VS Validation

Accuracy: Training VS Validation

Figure 9. Loss and accuracy as function of epochs (training time) for detecting a person. ***Loss decreases and accuracy increases with training time as expected. 100% accuracy can be achieved***

Fig. 10 shows the loss vs. validation as function of number of epochs (training time) when system tries to detect whether 0, 1, or 2 people are present. As in the previous cases, the accuracy increases as training time increases. Furthermore, the validation accuracy reaches 100% only after 40 epochs.

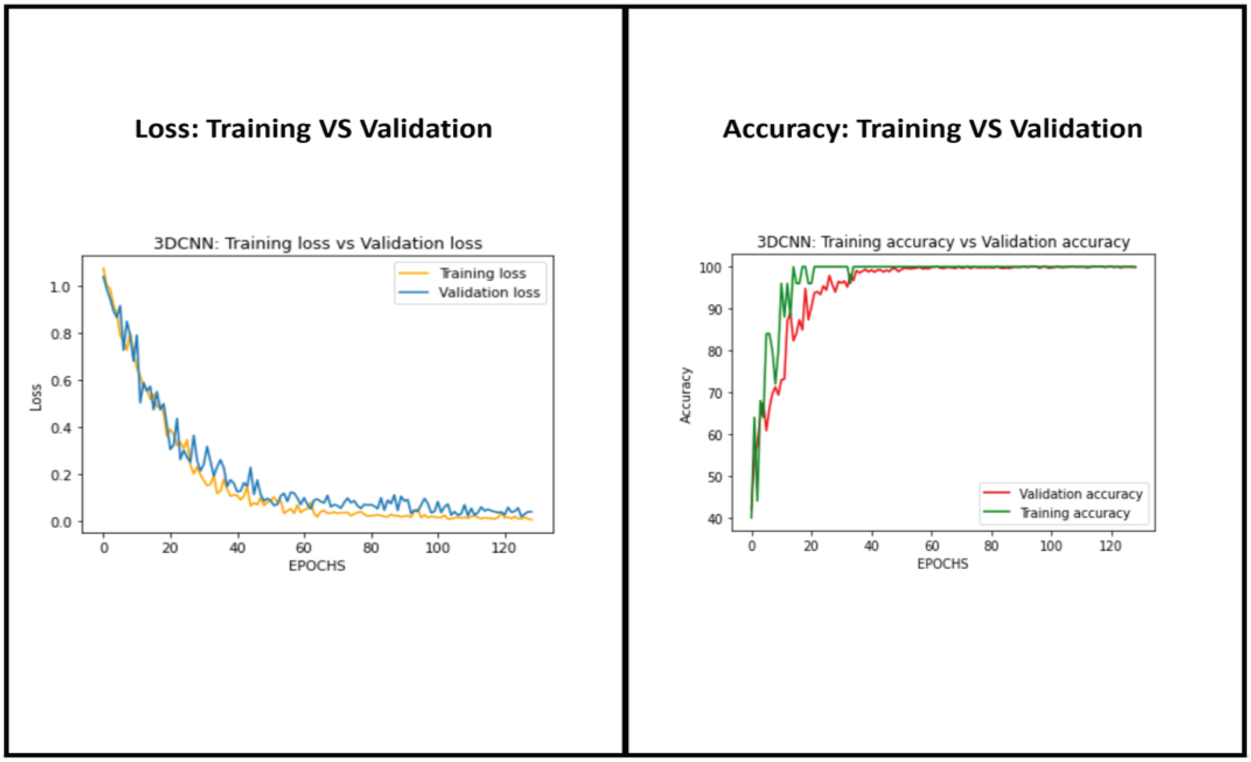


Figure 10. Loss and accuracy as function of epochs (training time) for detecting 0, 1, or 2 people. ***Loss decreases and accuracy increases with training time as expected. 100% of accuracy is achieved after training for 30 epochs***

Fig. 11 shows the loss vs. validation as function of number of epochs (training time) when system tries to detect whether 0, 1, 2, or 3 people are present. As in the previous cases, the accuracy increases as training time increases. Furthermore, the validation accuracy reaches 94% after 120 epochs.

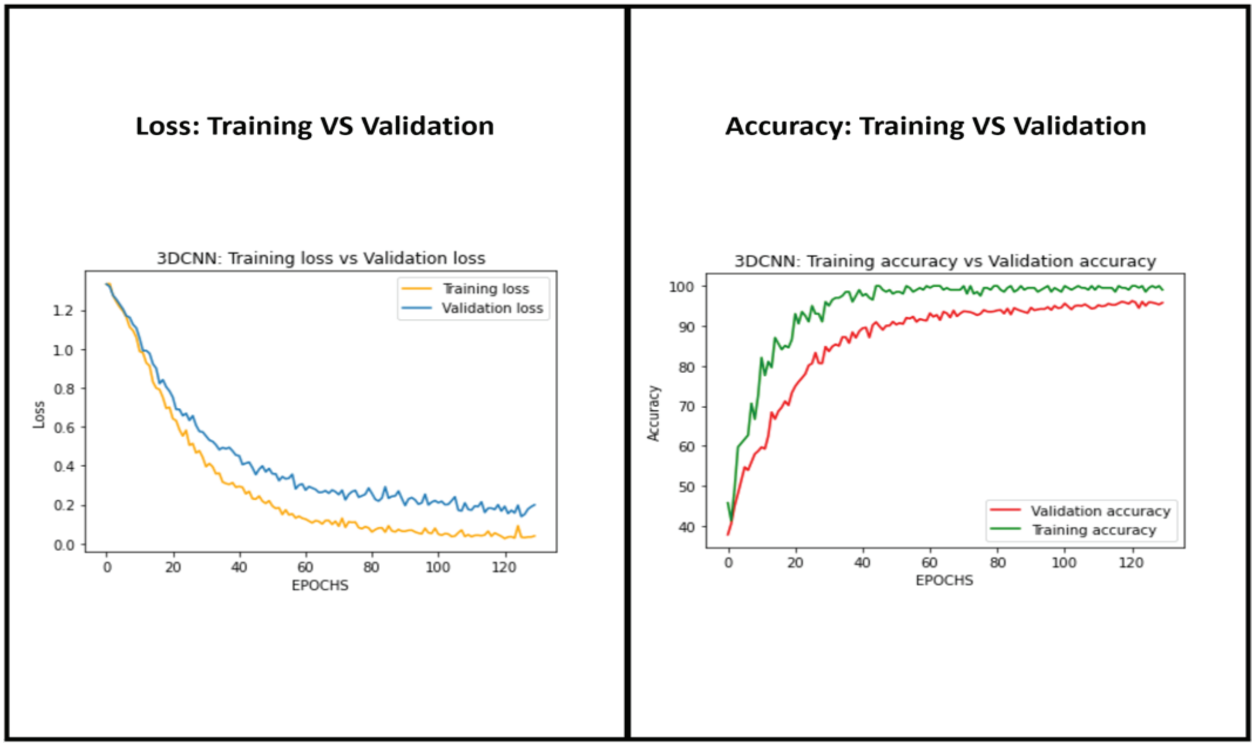


Figure 11. Loss and accuracy as function of epochs (training time) for detecting 0, 1, 2, or 3 people. ***Loss decreases and accuracy increases with training time as expected. Accuracy of 94% can be achieved after training for 120 epochs***

5. CONCLUSIONS

5.1 Active EMI Source-Passive Modulation Classification

As described in Section 4.1, the results for classifying different modulation types using CNN is mixed. The performance results are highly dependent on the channel characteristics as well as modulation types. With higher number of constellation points (> 1024) and low SNR (< 30 dB) and/or significant fading, high accuracy (> 95%) using a CNN, cannot be achieved. On the other hand, in limited scenarios where channel is line-of-sight and the QAM constellation size is not to large (< 1024), a CNN can classify the types of modulation accurately. These preliminary results indicate that for satellite communications, where channels are often line-of-sight, it might be possible to detect active naïve EMIs. However, it would be difficult to detect a capable EMI due to its ability to manipulate the channels.

5.2 People Counting System Using mmWave MIMO Radar

As described in Section 4.2, the proposed people counting system can determine the number of people in a typical room accurately (> 94%). We did not have enough time to build a more extensive database that can be tested for the cases of more than 3 people. It is interesting to note that the features input into the proposed CNN is quite small (< 20), but the proposed CNN is able to count the number of people accurately. Since the proposed CNN uses minimal number of features, it can be designed to be a low power device that can be potentially used to automate the data collection for advertisement, revenue projections as well as to adjust HVAC operations to reduce power consumption. In addition, these preliminary results indicate that it is possible to use a CNN to classify various moving objects or cluster of objects using their RF signatures in satellite settings given MIMO radar with sufficient resolution.

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