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Automatic Modulation Classification using Convolutional Neural Network

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ABSTRACT

With the increasing demands in the field of communication systems evolved the idea of cognitive radio, the design of an intelligent radio capable of sensing the channel conditions and hence deciding the optimal method of connection. Such systems are designed to operate over different channel conditions with different modulation schemes. A modulation classifier is an essential module in such systems and this paper proposes one such design based on convolutional neural networks. The proposed system tries to evaluate the performance of modulation classification over 3 different modulation classes over the Tensor Flow framework.

Keywords: Automatic modulation classification; Convolutional neural network; Tensor flow, Cyclo stationary features; Cognitive radio

1. INTRODUCTION

The recent developments in the field of fabrication technology, signal processing and computer science has led to great advances in wireless communication and this has made the electromagnetic spectrum a precious resource. There exists the need for development of efficient technologies that can optimally make use of the available spectrum to meet the growing demands. Research in the field of Cognitive Radios (CR) focuses on the development of reconfigurable radios capable of adapting to channel conditions and thus ensuring good quality of service irrespective of the dynamic nature of resource availability [1, 2]. Such a radio senses the channel conditions periodically and decides the optimal mode of communication to be set up. This should be supported by a system capable of generating data in any required modulation scheme; and at the receiver side it should have a system which can identify the modulation scheme of the received data and hence implement the corresponding demodulation algorithm to retrieve back the data. The block diagram for such a receiver architecture is shown in Fig.1. This need is supported by the developments in the field of Software Defined Radio which allows implementation of reconfigurable systems in software. The revolution of Digital Signal Processing replaced many of the conventional signal processing hardware to simple software modules easily implemented in some processor platform having the required computing capability. Earlier implementation of signal processing systems involved purely hardware designs which were to be implemented with high degree of precision to ensure good quality devices. The idea of implementing digital signal processing algorithms in software is easy to visualize and the capability to use such implementation in real time devices really simplified the design and made possible more cheaper and compact systems. With the multitude of embedded hardware and FPGA platforms available today, many such systems are now implemented in embedded platforms with a processor interfaced with necessary peripherals to form a complete signal processing system in itself. The design of previously discussed receiver can be easily realized in such a platform. A key component of such intelligent receivers is a modulation classifier capable of identifying the modulation scheme of the data it receives [3]. A lot of research is still

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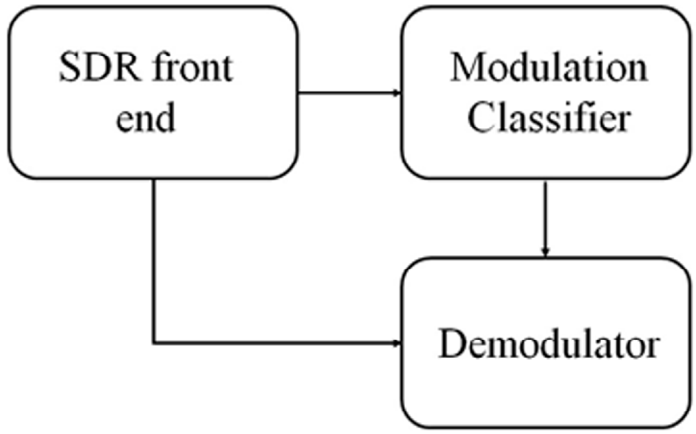


Figure 1: Typical receiver architecture

going on in this field for the development of a robust system which can operate successfully in the different scenarios to be practically expected. The primary challenge in this domain is the unpredictable nature of distortions introduced in the original signal as it gets transported over the channel. The channel parameters are highly time varying and random and hence there exists the need for a system that can identify the original signal characteristics buried deep in these distortions. This paper proposes a system for modulation classification based on the popular deep learning methodology of convolutional neural network implemented using the Tensor flow framework [4] .With the recent advancements in the field of deep learning [5] ,the field of neural networks has been heavily explored especially for applications in image and speech processing [6, 7, 8]. All these work have presented more intuition on the field and has made it possible to identify how the scheme can be applied to newer applications. Frame works like Tensor flow, Torch, Theano etc are tuned for developing deep learning algorithms and make possible the easy implementation and testing of such algorithms. (no 5 here) The proposed algorithm has been implemented using the Tensor flow frame work which comes with an optimized C++ back end providing efficient implementations of many optimization algorithms and a python API making the implementation simpler.

Section II of the paper discusses popular literature on the topic and presents popular algorithms so far proposed for modulation classification. The next section details neural networks, convolutional neural networks and the use of cyclostationary features for modulation classification. Section III discusses the implementation details. The results are presented in the next section and finally the conclusion is drawn in Section VI.

2. LITERATURE

A brief survey in the field of modulation classification shows that numerous algorithms has been proposed and tested in this field and they are popularly categorized as either likelihood based methods or feature based methods [9]. The former class of algorithms takes a probabilistic approach to identify the most probable modulation scheme from the probability density functions. In this category of methods the probability density functions of all the expected modulation schemes is used to calculate the probability of the received signal to be in any of the possible modulation scheme. This probability value is used as the indicator for prediction. This scheme of methods is shown to give satisfactory performance in high SNR environments whereas the addition of noise heavily degrades the signal and the probability measure can no longer serve as a reliable measure for robust prediction. Popular likelihood based classification algorithm includes average likelihood ratio test, generalized likelihood ratio test, hybrid likelihood ratio test and the quasi (average/hybrid) likelihood ratio tests. Panagiotu *et al* [10, 11] discuses summaries of all the above mentioned methods and provides comparison among the performance of these algorithms. The second class of classification methods extracts various features from the received signal to facilitate the classification.

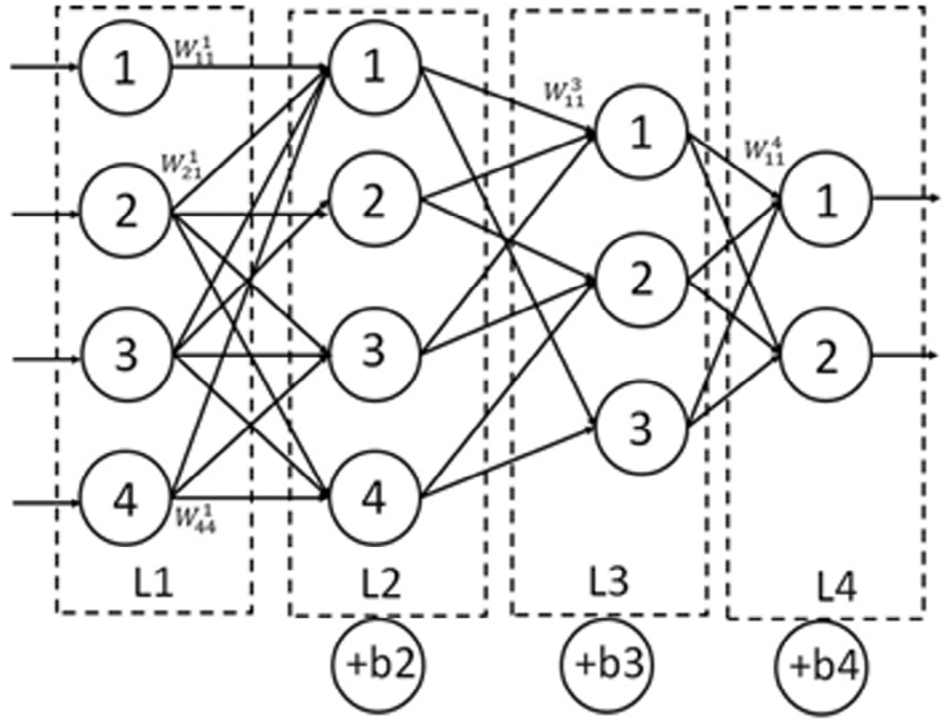


Figure 2: General neural network architecture.

This class of methods is based on the observation that signals belonging to different modulation schemes possess certain unique features which are prominently distinguishable even in the presence of noise and other disturbances. There are a lot of works available which examines the classification accuracy with different features and different classification algorithms. Narendar *et al* [12] discusses one such method based on fractional lower order statistics (FLOS); forth order cumulants were chosen as the feature for classification and the method is shown to have better performance as compared to the earlier methods in terms of fidelity to noise and fading conditions. Ahn *et al* [13] proposes the use of higher order cumulants and presents a classification algorithm based on gaussian mixture models. The statistical parameters of modulation signals have an inherent periodicity; the details of which can be captured in the spectral correlation function of these signals. Several literature [14, 15] discusses classification algorithms based on these cyclic cumulants as features.

Neural networks has been extensively applied in a variety of pattern recognition and regression problems across domains [16]. Earlier, the only reason preventing the use of artificial neural networks in real time problems was the heavy computational requirements for their optimal performance and the problem is more or less tackled today with the introduction of platforms with FPGAs and GPUs capable of handling bigger problems in a smaller platform [17]. Also there is plenty of literature discussing variety of applications where artificial neural network and convolutional neural networks has been successfully applied for classification problems [18, 19, 20].

3. THEORY

3.1. Neural Network for Modulation Classification

Humans were always fascinated by their own ability to think and make decisions and are really proud of this ability. As our demands increase, humans are in need of systems which could think for themselves and adapt themselves based on experiences as living beings do. It was the attempt to imitate the human brain that developed the field of neural networks. The whole system can be visualized to have several nodes interconnected in such a way that they can learn operations they are trained for. In detail, the network

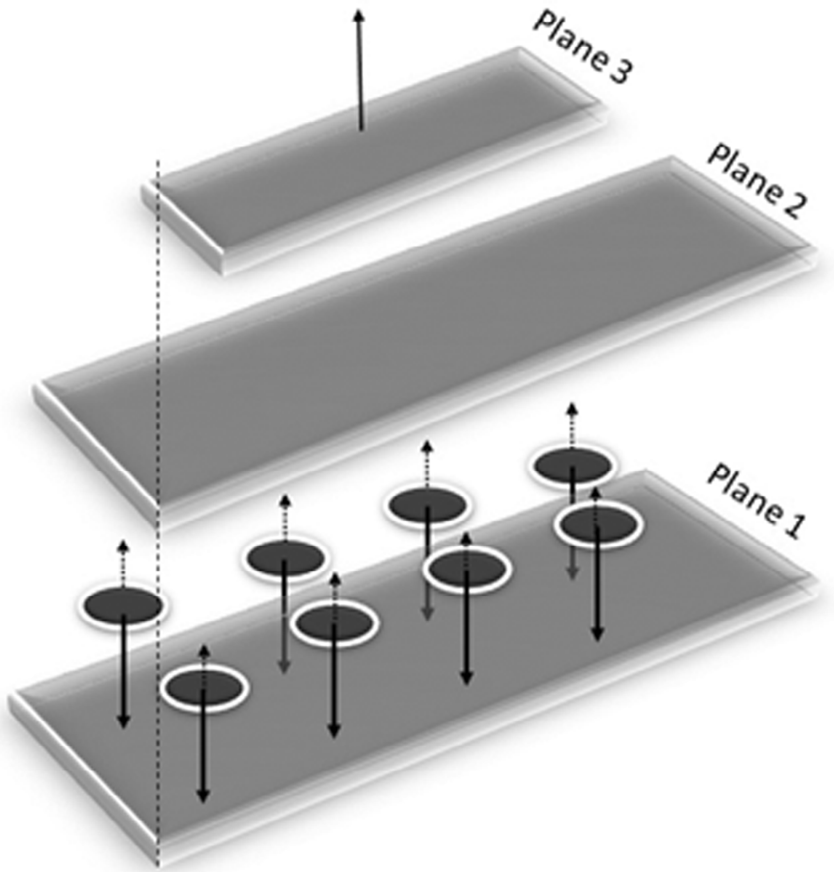


Figure 3: General convolutional neural network architecture

essentially consists of an input layer and an output layer with any number of optional hidden layers in between. Each layer consists of nodes (also called neurons) connected to some or all of the nodes of the next layer by some weights. For example in Fig. 2 *L1* is the input layer, *L4* is output layer and *L2* and *L3* are the hidden layers. Here, W_{ij}^{L} represents the weight of the net connecting i^{th} node in layer L to the j^{th} node in layer $L + 1$. b_L is the bias applied to layer L. These weights and biases are responsible for mapping the input to the output. The output of each node is sum function of the weighted sum of the outputs of all the previous nodes and the bias of that layer; the weights W_{ij}^{L} being the corresponding net weights . The function acting on the weighted sum is called the activation function. For instance, in Fig. 2 in layer 2, the output of node 1 can be represented as in Eq.1.

$$h_1^2 = g(\sum_{i=0}^{4} W_{i1}^1 h_i^1 + b_L) \tag{1}$$

where g is the activation function. Common choices of activation function includes the sigmoid function, tanh, RELU(Rectified Linear Unit) etc. The need here is to learn that set of optimal weights and biases which would produce the correct output for all the inputs available in the training set. The weights and biases are initialized either randomly or with some apriori information [21, 22, 23] and the network is fed with one sample test data. The corresponding error in the output is calculated using some chosen loss function and then the mechanism of back propagation is used to readjust the parameters to decrease errors. In back propagation, the error in each stage is back calculated starting from the output layers. The error in each node is then added to the corresponding weights and biases scaled by some learning rate. This makes it clear that the efficiency of a neural network heavily depends on the proper training and a good training set can ensure dependable performance from the network.

According to the above discussed architecture the input to the neural network is expected to be a one dimensional vector of data points. However, in cases where the data is multi-dimensional (eg. in images, in modulation data (I & *Q* streams)) it is always preferred to go for some architecture capable of extracting the spatial correlation in data. These features are really critical in identifying the behavior of the data and such an architecture is used in convolutional neural networks. A typical convolutional neural network architecture is shown in Fig. 3.

Here, plane 1 can represent a typical input layer for a convolutional network. The elements of plane 1 are locally processed by the weights and biases and then acted upon by the activation function; all of which are represented by the circles in Fig.3. This operations result in plane 2 which can be dimension different from plane 1 depending on whether zero padding was done prior to the convolution operation (filtering using the weights). Plane 2 may further be down sampled based on some criteria to form plane3 which can be again be the input to another convolutional layer or another fully connected layer.

This paper proposes a convolutional neural network architecture for modulation signal classification. The result corresponding to the input being a two dimensional vector consisting of *I* & *Q* stream data, and also the case for the input data appended with cyclo stationary features is studied.

3.2. Cyclostationary features for AMC

Modulation signals belongs to the class of cyclostationary signals; signals whose statistical parameters exhibits a periodicity [24]. The periodicity of these parameters are not discernible from the power spectral density of these functions, however there exists some quadratic transformations which can transform these cyclostationary signals to signals with first order periodicity [25, 26]. In general, the mean and autocorrelation function of cyclostationary signals can be expressed as in Eq. 2.

$$\begin{aligned} \mu_x(t+T) &= \mu_x(t) \\ \chi_x(t+T,\tau) &= \chi_x(t,\tau) \end{aligned} \tag{2}$$

The spectral correlation function (SCF) of a function captures the correlation between the spectral components of a signal and are observed to be unique for signals of different behavior. In the case of modulation signals especially it has been observed that signals belonging to different modulation schemes have very different SCF's and thus can effectively be used as features capable of distinguishing between different modulation schemes [26]. As per Wiener Khinchin theorem for cyclostationary signals, the spectral correlation function of these signals is the Fourier transform pair of the cyclic auto correlation function (CAF). Thus the spectral correlation function can be expressed as in Eq. 3.

$$\psi_x^\alpha(f) = \int_{-\infty}^{\infty} \chi_x^\alpha(\tau) e^{-i2\pi f\tau} \tag{3}$$

where the cyclic auto correlation function being periodic can be expressed as the Fourier series expansion in Eq. 4 with Fourier coefficients given by Eq. 5.

$$\chi_x(t,\tau) = \sum_{\alpha} \chi_x^\alpha(\tau) e^{i2\pi\alpha t} \tag{4}$$

$$\chi_x^\alpha(\tau) \triangleq \lim_{T\to\infty} \frac{1}{T} \int_{-T/2}^{T/2} \chi_x(t,\tau) e^{-i2\pi\alpha t} dt \neq \tag{5}$$

Also, [27, 28] shows that the SCF can equivalently be derived from the spectral cross correlation, i.e. the SCF can be estimated from the correlation between two spectrally shifted versions of the original

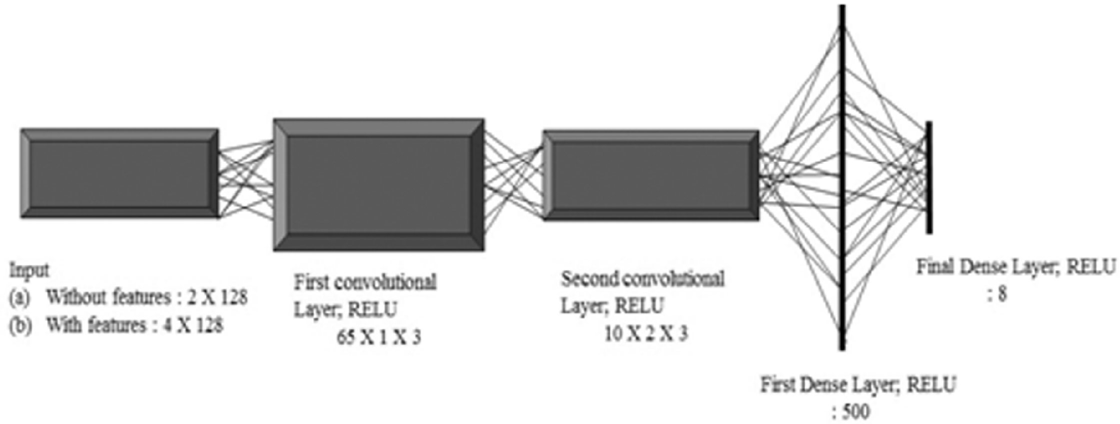


Figure 4: Evaluated convolutional neural network architecture.

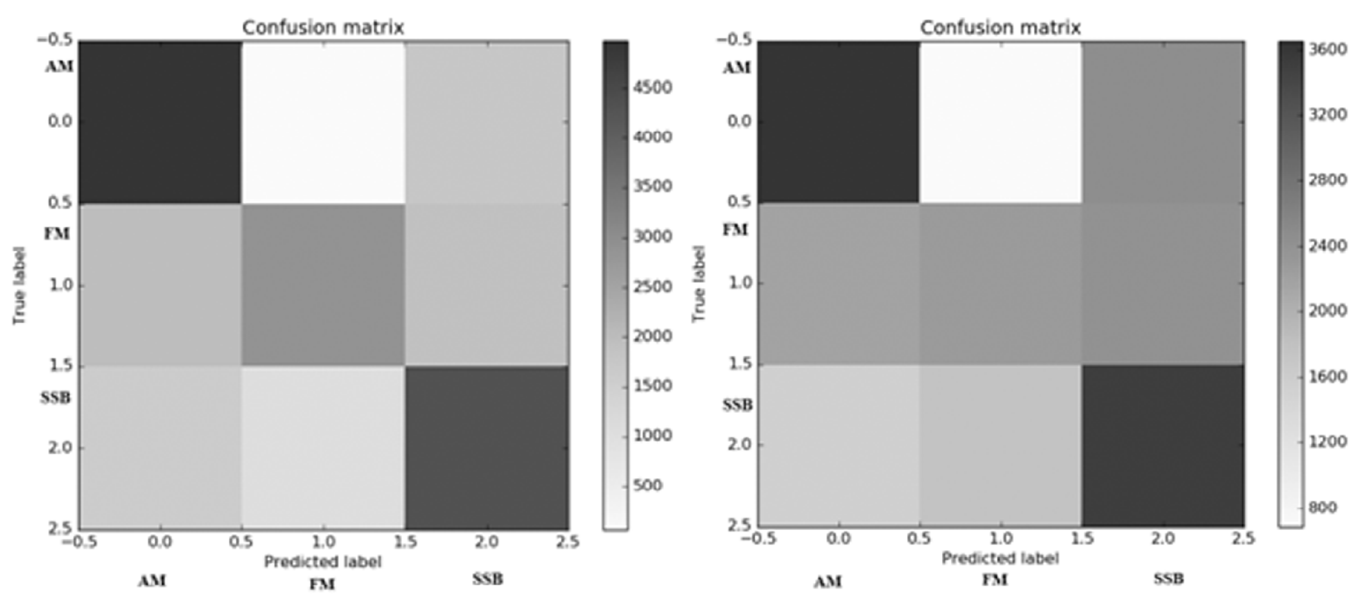
spectrum. S_x^α can be estimated from the correlation of the signal at frequencies alpha apart. Gardner *et al* [27] gives the following approximation for SCF from the instantaneous value of SCF by applying a smoothing function as given by Eq. 6.

$$\psi_x^\alpha(f) = \lim_{\Delta t, T\to\infty} \frac{1}{\Delta t} \int_{-\Delta t/2}^{\Delta t/2} X_T(t, f+\frac{\alpha}{2}) X_T^*(t, f-\frac{\alpha}{2}) dt \tag{6}$$

From, Eq. 6 The paper compares the accuracy and performance of modulation classification of *I & Q* stream data with and without cyclostationary features appended.

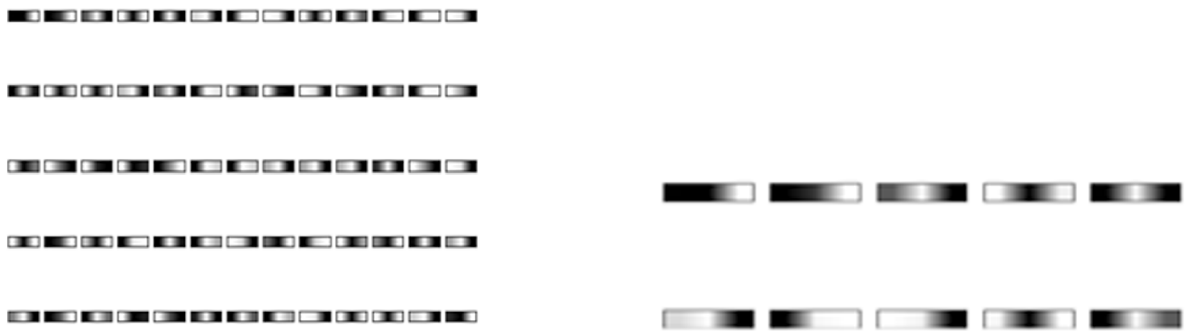
4. IMPLEMENTATION DETAILS

A four layer convolutional neural network with two convolutional layers and two fully connected layers was implemented. Similar networks were already evaluated for classification without features [29]. The



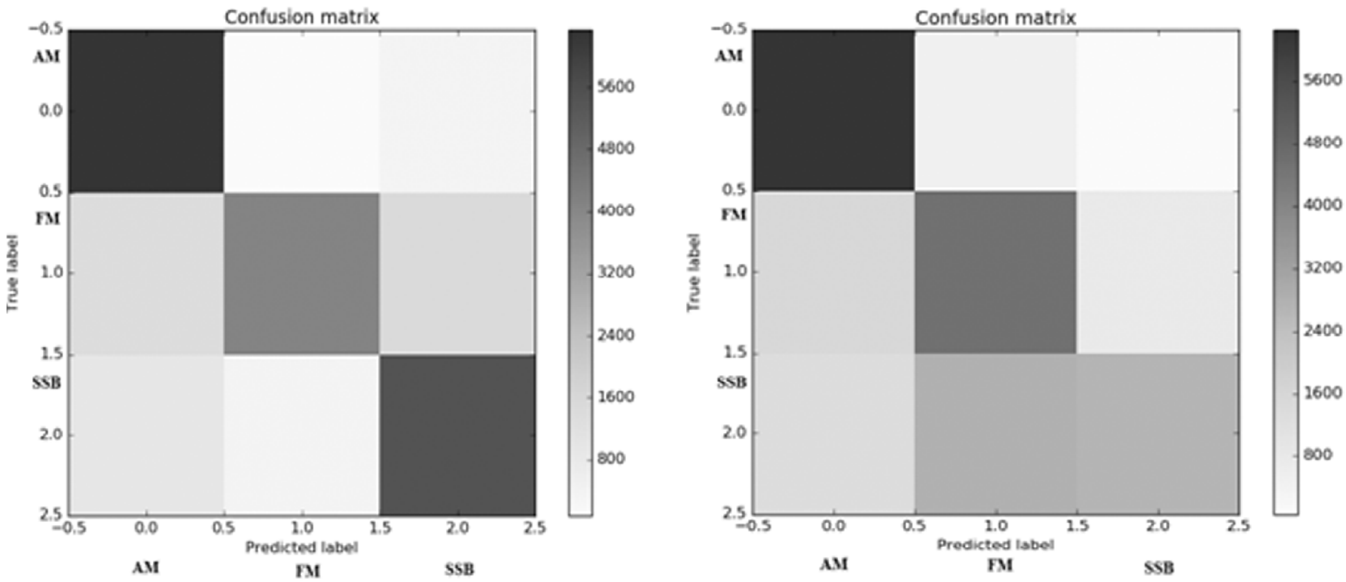
(a) SNR = 16dB **(b) SNR = 10dB**

Figure 5: Confusion matrices for classification without features



(a) Layer 1 weights **(b) Layer 2 weights**

Figure 6: Weights for classification features at SNR = 10dB



(a) SNR = 16dB **(b) SNR = 10dB**

Figure 7: Confusion matrices for classification with features

corresponding network with weight dimensions is shown in Fig. 4. Convolutional neural network was chosen to make use of the relation between the corresponding samples in the *I & Q* streams. The *I & Q* streams were fed into the network as a two dimensional vector in the form of discrete frames each 128 samples wide. Further half of each frame was made overlapping with the previous frame. The first two convolutional layers implemented 65 and 10 number of filters. The first layer was implemented with a one dimensional filter and the second with a two dimensional filter. The neural network is expected to learn these filter weights over the training process such that they extract essential features from the signal which are capable of distinguishing between the different modulation schemes. The rectified linear activation function was chosen as the activation function for these two convolutional layers. Further the information extracted from these features are used to predict the label corresponding to the data point by adjusting the weights and biases across the next two fully connected layers, the first implemented with a rectified linear activation function and the second with a soft max function for activation. The error function for back propagation was chosen as the difference between the predicted and original class labels added with regularization parameters to avoid over fitting. Regularization was achieved by minimizing the l_2 norm of the weight variables in all layers and the l_1 norm of the first dense layer. The optimization function was solved using the Adams method an algorithm for stochastic gradient descent. Further drop out was done during training to avoid over fitting. The whole network was implemented and tested on the Tensor flow framework.

5. RESULTS

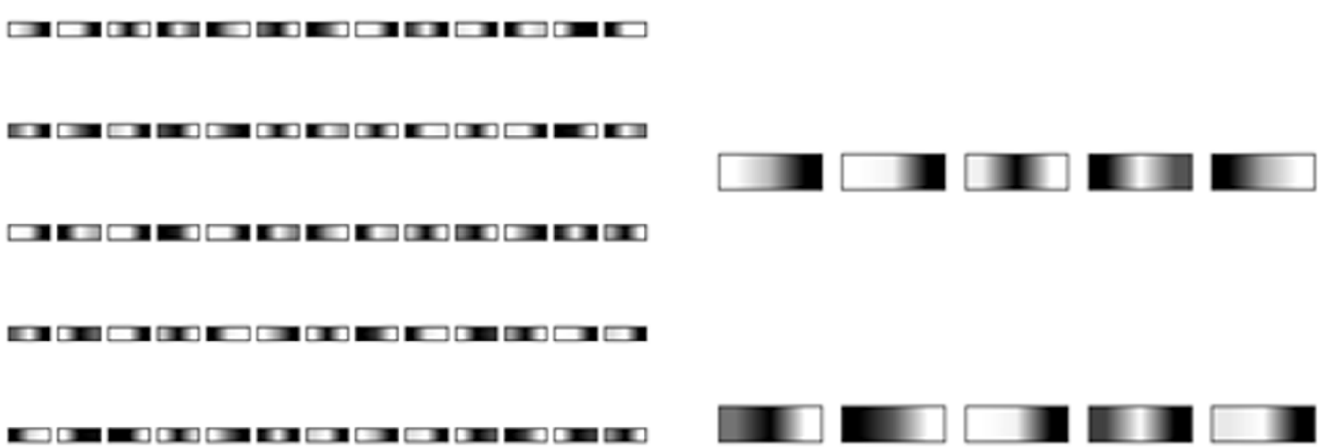
The performance of the network was tested on a synthetically generated dataset. I & Q samples corresponding to three analog modulation schemes: double side band amplitude modulation, single side band modulation and frequency modulation were generated for two different SNR conditions using the GNU radio platform [30]. Noise was introduced to the signal using the channel models available here.

5.1. Classification without features

Initially classification of data without any features was tested on data sets at SNR conditions of 16 dB and 10dB. Fig. 5 shows the resulting confusion matrices after classification was tested on sample *I & Q* frames. It shows that the accuracy of classification decreases with increase in noise and there is more misclassification of single side band modulation as double side band modulation which can be due to the similarities in the two schemes. Fig. 5a and Fig. 5b shows the layer 1 and layer 2 weights learned after training data of SNR 16 dB. They show that different filter weights are learned in both the situations although the exact features captured are not directly discernible. They were both trying to extract slightly different features from the data. An average classification accuracy of 60 - 62% was observed.

5.2. Classification with features

The network was then fed with data appended with two rows of features corresponding to the real and imaginary parts of cyclostationary features extracted from the I stream data of the respective frame. Fig. 7a and Fig. 7b shows the resulting confusion matrices from classification under SNR conditions of 16dB and 10dB respectively. Further, Fig. 8a and Fig. 8b shows the layer 1 and layer 2 weights. Comparing these with the previous case of data without features shows that the filters are slightly different although the exact features extracted in both the cases are not explicitly discernible from the figures. Since, the network is now introduced with a different picture of the data, the filters are expected to be different as they are looking for different features capable of classifying the data. The confusion matrices show significant improvement in classification with the addition of features to the data frames. This can be due to the additional features that can be extracted from the frequency domain profile of these signals. Further, the classification remains better robust under noise conditions because the cyclostationary features are not too effected by noise. Also, the average classification accuracy was 70 - 72% in these cases.



(a) Layer 1 weights (b) Layer 2 weights

Figure 8: Weights for classification features at SNR = 10dB

6. CONCLUSION

The proposed convolutional neural network architecture is capable of classification between the three analog modulation schemes namely double side band amplitude modulation, frequency modulation and single side band modulation. Further, when the average accuracy of classification of data was 61%, it was found to increase to 71% with the addition of cyclostationary features. The method shows high scope for research and could be extended to the classification of analog as well as digital modulation schemes.

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