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The Instinctive Cognizance Of Deep Learning Architecture For Analog And Digital Modulation Schemes

Winny Elizabeth Philip [1], Hari.S [2]

[1]*(Department of Electronics and Communication Engineering, Mount Zion College of Engineering, Kadammanitta,Pathanamthitta,Kerala,India)*
[2]*(Department of Electronics and Communication Engineering, Mount Zion College of Engineering, Kadammanitta,Pathanamthitta,Kerala,India)*
Corresponding Author: Winny Elizabeth Philip

Abstract : *We present an automatic modulation recognition work for the identification of radio signals in a communication network. Our aim is to design an efficient communication system and make the receiver is capable to detect the modulation scheme of the signal it receives, using Automatic Modulation Recognition without having minimum or earlier knowledge of the transmitted signal.The work consider both SVM and ANN architectures and finally observe the efficient learning tool for recognition. Initially we classify the modulation schemes using non linear SVM. After that, we use Artificial Neural Network(ANN) for further classification of analog and digital modulations. Features were also extracted using wavelet decomposition and fast fourier transform techniques. Neural Networks were applied to the extracted features to distinguish between signals having different modulation schemes.*

Keywords: *Artificial Neural Network, Modulation recognition, Support Vector Machine, Wavelet decomposition.*

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I. INTRODUCTION

The modern world is quickly moving towards a more intelligent and efficient communication system. To attain efficient data transmission, different modulation methods in a communication network uses generally modulated transmitted signals. It is an intermediate process between signal detection and signal demodulation. Modulation recognition is an important technology to provide modulation information of signals. Automatic modulation recognition (AMR) provide quite a bit of flexibility in dealing with different communication standards. A single receiver circuit can be helped to detect different modulation schemes and then demodulate those signals. This technique can also be used in different way such as interference identification, signal confirmation and spectrum management. Knowledge of which modulation scheme is used can provide valuable information and is also crucial in order to retrieve the information stored in the signal. Modulation recognition can be used for electronic warfare purposes like threat detection analysis and warning in the military domain. It can further assist in the decision of appropriate counter measures like signal jamming. Modulation recognition is also believed to play a significant role in future 4G software radios.

II. RELATED WORK

Basically, modulation recognition methods are divided into two types: decision theory based method and statistical pattern recognition based method. In the decision theory based methods,[1]-[3] for solve the problem of modulation recognition it uses probability theory, hypothesis testing theory and a proper decision criterion. However, this method requires the prior information of received signals, it is time-consuming and inefficient when a large number of modulation types exist. Another approach is pattern recognition problem, statistical pattern recognition approaches are capable of learning a recognition model multiple unknown parameters based on sufficiently large training data. Thus, we can provide simultaneously the complete information of different modulations in training data and considering some expert features. This approaches are more robust and efficient. This methods normally focus on feature extraction and classification algorithms.

The usually used feature extraction methods are instantaneous amplitude, frequency and phase[4], high-order statistics (HOS)[5], cyclostationary characteristics[6],and the decision tree[7]which are existing classifiers, support vector machine [8](SVM),and artificial neural network[9]. Recently, the deep learning tool is well studied in image classification[10], object detection [11]and speech recognition process[12]. It has also attracted great application [13]and been applied in modulation recognition and it also convert the modulated signals into constellation diagrams and feed them to the Alexnet model to perform classification. Another paper proposes a signal recognition algorithm [14] for blind digital modulation identification, based on high order statistics and the extreme learning machine (ELM), To pre-process signals the paper uses cyclic spectrum[15], then compares the recognition performance of a deep auto encoder network with those of the three algorithms including SVM, naive Bayes and neural network.

The paper surveys the important[16] applications of machine learning in radio signal processing domain and it uses GNU Radio[16] to generate an open dataset with raw In-Phase and Quadrature (IQ) information for modulation recognition. The paper studies the adjustment[17] of convolutional neural networks (CNN) to the dataset in and compares the modulation recognition performance of the proposed CNN against those of the expert cyclic moment features based methods. Furthermore, in the authors make a comparison between [18] CNN, residual networks, inception modules, convolutional long short-term deep neural networks(CLDNN) based on the dataset in and experimental results show that modulation recognition performance is not limited by network depth. The paper [19] check the applicability of the CNNs and the Long Short Term Memory (LSTM) networks for modulation recognition, since the CNNs are good at extracting features of spatial data and the LSTM networks have been proved to behave well in sequence data.

In this paper[20] we evaluate the applicability of various Neural network for modulation recognition. We use support vector machine(SVM) tool for initial classification and further use Artificial Neural Network.SVM are capable of handling small number of data samples.Initially, features are extracted by using Fast Fourier Transform and wavelet decomposition method.After that we concentrate only wavelet based feature extraction. We evaluate the recognition performance of the 8 digital modulation schemes and 5 analog modulation schemes by using dataset created by Graphical User Interface(GUI). Moreover, the recognition performance of the proposed framework is compared with other neural networks.

III. PROPOSED SYSTEM

The paper needs to design an efficient communication system and the receiver has the ability to detect the type of the modulation of the signal it receives, using Automatic Modulation Recognition (AMR) algorithms, without having any earlier knowledge of the transmitted signal and analyze the incoming signal;extract information which can be used by the algorithm to identify the modulation scheme.

1. To develop a transmitter capable of transmitting 8 digital modulation schemes,5 analog modulation schemes and a receiver capable of recognizing and demodulation them. The eight digital modulation schemes are ASK,BPSK,DPSK,FSK,M8PSK,OOK,QAM,QPSK and the five analog modulation schemes are AM,FM,PM,PPM and PWM.
2. Develop various methods for extraction of different key features from the received signal which can be helped for distinguishing different communication signals.
3. Develop algorithms for modulation recognition are based on key features extracted from the signal using Artificial Neural Networks (ANN) approach.
4. Develop demodulators capable of demodulating the recognized modulation scheme.

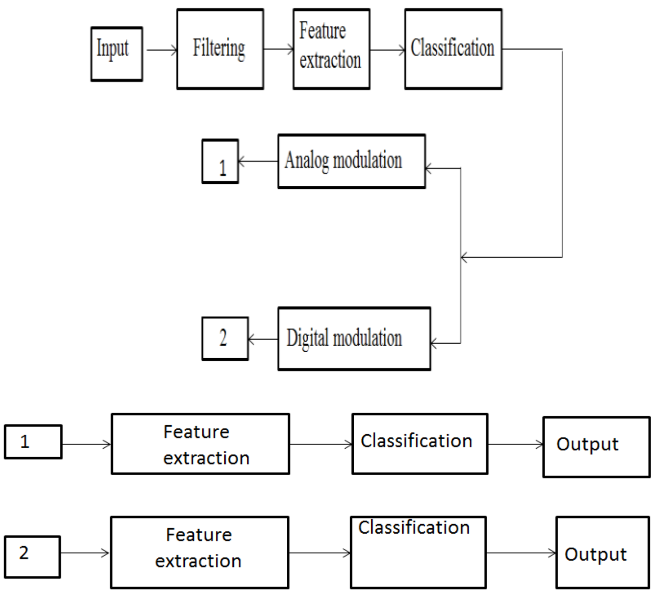

Fig.1: Block Diagrams of the recognition system

Initially the samples are given to the filters for noise reduction. Then the features are extracted by using wavelet decomposition and fast fourier transform used to identify the most important features. After this feature extraction, the input is given to the classifier ANN. It is a learning model associated with learning algorithm. The classifier detects whether it is analog or digital modulation.

A neural network acquires knowledge through learning. A neural network's knowledge is stored within the inter-neuron connection strengths known as synaptic weights. ANNs are considered as a wave of future in computing. These are self-learning processes which don't require the help of traditional skills of a programmer. The usefulness of artificial neural networks has been demonstrated in several applications such as diagnostic problems, medicine, speech synthesis, robot control, business and finance, signal processing, and other problems that fall under the category of pattern recognition.

IV. ADVANTAGES OF NEURAL NETWORK

Whether its humans or other computer programs, they can use neural networks with their ability to make sense of complicated or imprecise data, to detect patterns that are too hard to be noticed. A trained neural network can be considered as an expert in the specific task whose information has been given to it. Advantages include:

- **Self Organization:** An artificial neural network can create its own organization from the information it acquires during learning time.
- **Adaptive Learning:** It has the ability to learn how to implement tasks based on the given data for training.
- **Real Time Operation:** All computations in ANN is carried out by parallel. This advantage of capability is taken by the hardware devices.
- **Fault Tolerance via Redundant Information Coding**: Even small problems in a network can reduce the performance accuracy. However, some network have the ability to maintained even with the major network damage.

V. EXPERIMENT

In this experiment, we create the dataset using Graphical User Interface(GUI). The dataset contains 8digital modulation methods ASK,BPSK,DPSK,FSK,M8PSK,OOK,QAM,QPSK and the five analog modulation schemes are AM,FM,PM,PPM and PWM. which are widely used in wireless communication systems. The purpose of modulation is to take a message signal and superimpose it upon a carrier signal. The carrier signals are chosen to be on high frequency because of several reasons:

- For easy propagation (low loss and dispersion)
- So they can be transmitted simultaneously without interfering with other signals.
- To enable the construction of small antennas.
- To enable multiplexing (combine multiple signals and send them at the same time).

The simulations performed for this project have been carried out in MATLAB. The entire project has been divided into three parts

- Feature Extraction
- Main Program
- Recognition Process

The data for training and testing is separately written into two files name "Training" and "Testing". Before the data is divided into separate files, we take decision on how much the number of total sample is. Signal of a specific type is produced and noise is added to it. Next, feature extraction is done and finally the feature vector of the signal is written to the corresponding file depending on whether it is a training sequence or a testing one.

Features Extraction

It is a very crucial step for any recognition problem. To train any system we need to represent every sample by its representative feature set. Many feature extraction processes are described for modulation signal recognition. The modulation recognition process based on neural network requires testing different architectures in order to reach an acceptable decision accuracy.

Training Phase

The main goal of the training phase is for the network to find the optimum weights and biases to minimize the error between the network output and the correct decision. There are different methods for reduction of the error namely Back propagation, Hebbian learning, competitive learning etc. A well -known criteria is the minimum mean squared error between the network output and correct decision. Also, there are different types of learning such as supervised, unsupervised and self-organized learning.

VI. RESULT

Fig2,3and4 shows the recognition performance efficiency of SVM and ANN using confusion matrix. Fig.2 shows that efficiency of SVM. The Support Vector Machine used in the initial phase of our experiment. In the confusion matrix matrix of SVM,we got overall 92.4% efficiency.

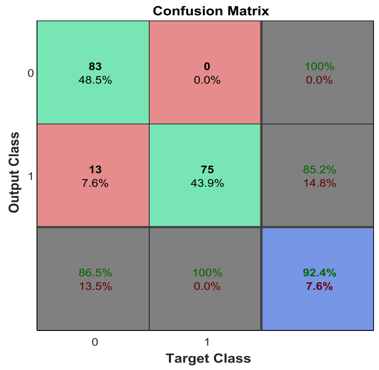

Fig.2: Efficiency of SVM using confusion matrix

Another learning tool for modulation recognition is Artificial Neural Network(ANN).it is more efficient than SVM.Fig.3 shows that efficiency of analog modulation recognition using ANN.In this matrix,we take PWM and PPM are uniquely. The total recognition accuracy of the system is 86.0%.

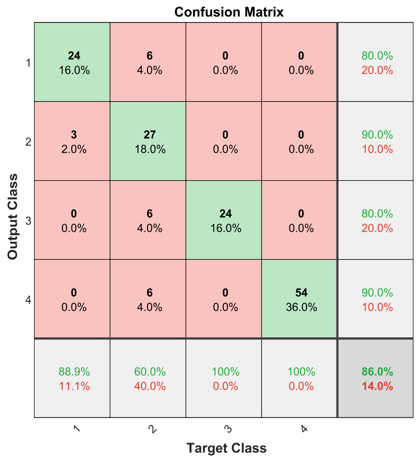

Fig.3: Efficiency of ANN using confusion matrix in analog modulation

Similarly in the fig.4 shows that efficiency of digital modulation using ANN. Overall system efficiency is 86.5%.we give 8 inputs as target class. Confuion matrix is a matrix it shows the efficiency, when we give an input,then it shows the efficiency for probability of detect the same input.in any target class detects wrong detection,then efficiency decreases.

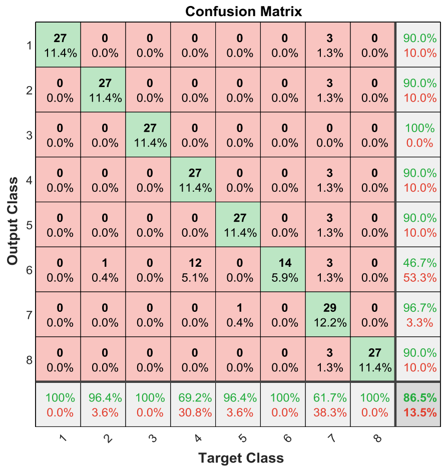

Fig.4: Efficiency of ANN using confusion matrix in digital modulation

From this experiment we can recognise modulation type and which type of modulation is belongs to. Fig.5 and 6 shows the example of modulation recognition of analog and digital modulation.

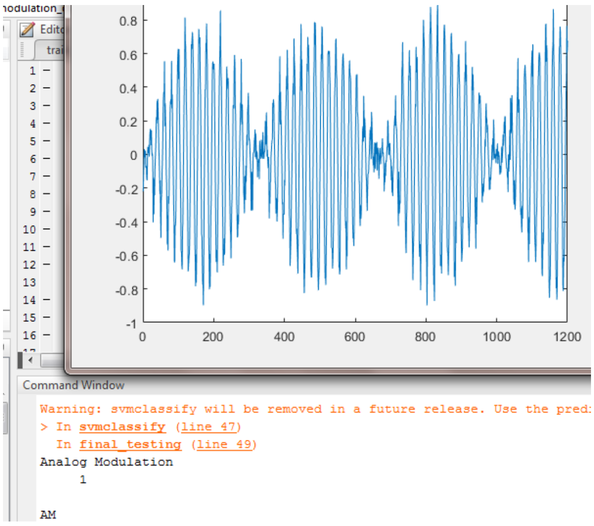

Fig 5: Modulation recognition of analog AM modulation using ANN

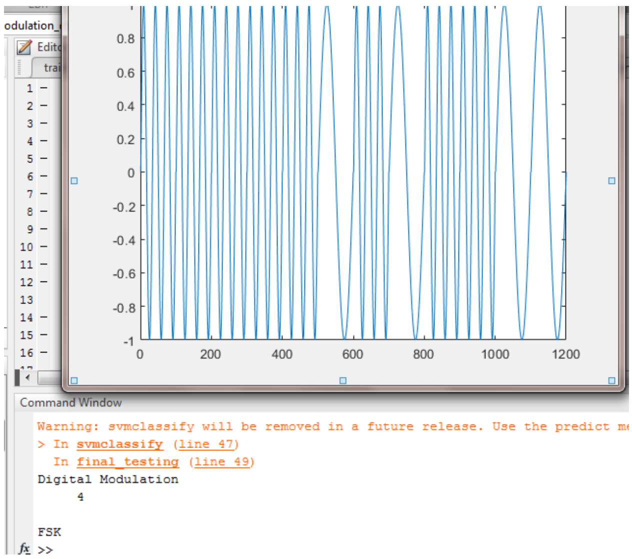

Fig.6: Modulation recognition of digital FSK modulation using ANN

VII. CONCLUSION

From the performance shown in this chapter by different networks such as SVM and ANN clearly reveal that the number of hidden layers and the neurons within them play a very important role in the recognition rate of the signals.We can implement SVM for initial operations and then after we use ANN for modulation recognition.because ANN is more efficient than SVM.It recognizes the 5 analog data and 8 digital data.

In our future work,we can find out the modulation index of these signals and can also apply various classifiers for more accuracy. Ongoing research investigators can implement a perfect recognition accuracy system in extremely noisy scenarios.

References

[1]. Wen Wei and J. M. Mendel, "Maximum-likelihood classification for digital amplitude-phase modulations," *IEEE Transactions on Communications, vol. 48, no. 2, pp. 189–193, Feb 2000.*

[2]. J. A. Sills, "Maximum-likelihood modulation classification for psk/qam," in MILCOM 1999. *IEEE Military Communications. Conference Proceedings (Cat. No.99CH36341), 1999, vol. 1, pp. 217–220 vol.1.*

[3]. Chung-Yu Huan and A. Polydoros, "Likelihood methods for mpsk modulation classification," *IEEE Transactions on Communications, vol. 43, no. 2/3/4, pp. 1493–1504, Feb 1995.*

[4]. A. K. Nandi and E. E. Azzouz, "Algorithms for automatic modulation recognition of communication signals*," IEEE Transactions on Communications, vol. 46, no. 4, pp. 431–436, Apr 1998.*

[5]. A. Swami and B. M. Sadler, "Hierarchical digital modulation classification using cumulants," *IEEE Transactions on Communications, vol. 48, no. 3, pp. 416–429, Mar 2000.*

[6]. Liang Hong, "Classification of bpsk and qpsk signals in fading environment using the ica technique," *in Proceedings of the Thirty-Seventh Southeastern Symposium on System Theory, 2005. SSST '05., March 2005, pp. 491–494.*

[7]. S. R. Safavian and D. Landgrebe, "A survey of decision tree classifier methodology," *IEEE Transactions on Systems, Man, and Cybernetics, vol. 21, no. 3, pp. 660–674, May 1991.*

[8]. Bernhard Sch?lkopf, Koji Tsuda, and Jean-Philippe Vert, Advanced Application of Support Vector Machines, *pp. 275–275, MIT Press, 2004.*

[9]. R. Lippmann, "An introduction to computing with neural nets," *IEEE ASSP Magazine, vol. 4, no. 2, pp. 4–22, Apr 1987.*

[10]. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, "Imagenet classification with deep convolutional neural networks*," in Advances in Neural Information Processing Systems 25, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds., pp. 1097–1105. Curran Associates, Inc., 2012.*

[11]. Ross Girshick, "Fast r-cnn," *Santiago, Chile, 2015, vol. 2015 International Conference on Computer Vision, ICCV 2015, pp. 1440 – 1448,* Convolutional networks;Detection accuracy;Open sources;Regionbased; Test time;Training and testing;.

[12]. A. Graves, A. r. Mohamed, and G. Hinton, "Speech recognition with deep recurrent neural networks," *in 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, May 2013, pp. 6645–6649.*

[13]. S. Peng, H. Jiang, H. Wang, H. Alwageed, and Y. D. Yao, "Modulation classification using convolutional neural network based deep learning model," *in 2017 26th Wireless and Optical Communication Conference (WOCC), April 2017, pp. 1–5.*

[14]. X. Liu, C. Zhao, P. Wang, Y. Zhang, and T. Yang, "Blind modulation classification algorithm based on machine learning for spatially correlated mimo system*," IET Communications, vol. 11, no. 7, pp. 1000– 1007, 2017.*

[15]. J. Li, L. Qi, and Y. Lin, "Research on modulation identification of digital signals based on deep learning*," in 2016 IEEE International Conference on Electronic Information and Communication Technology (ICEICT), Aug 2016, pp. 402–405.*

[16]. T. O'Shea and N. West, "Radio machine learning dataset generation with gnu radio*," in Proceedings of the GNU Radio Conference, 2016, vol. 1.*

[17]. T. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," *Aberdeen, United kingdom, 2016, vol. 629, pp. 213 – 226.*

[18]. N. E. West and T. O'Shea, "Deep architectures for modulation recognition,"*in 2017 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN), March 2017, pp. 1–6.*

[19]. S. Hochreiter and J. Schmidhuber, "Long short-term memory*," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.*

[20]. Automatic Modulation Recognition using Deep Learning Architectures. Meng Zhang, Yuan Zeng, Zidong Han and Yi Gong, *senior member, IEEE Southern University of Science and Technology,2018.*