International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Automatic Modulation Identification in Receiver Environment Using Machine Learning Techniques

M. Mani Kumar Reddy[1], B. Narasimha Reddy[2], K. Ravi Sankar[3], G. Krishna Murthy[4]

[1,2,3,4]Assistant Professor (Adhoc), Department of ECE, JNTUA College of Engineering, Pulivendula.

Abstract
Many communication applications, particularly military ones, have a major demand for security. An adaptive radio system (ARS) with adaptive modulation provides security, interference control, and efficient transmission in these circumstances. In response to spectrum sensing and channel estimates, the adaptive modulator modifies its modulation schemes and carrier frequency. An adaptive receiver however offers signal authentication, validation, and the selection of an appropriate demodulation method in electronic warfare. A crucial first step in the deployment of Cognitive Radio (CR) is the design of smart receivers. The performance of the intelligent receiver is assessed by Automatic Modulation Identification of the received signal. Modern wireless communication relies heavily on automatic modulation Identification [1]. In this investigation Four classifiers namely Decision Tree, Support vector machine, k- Nearest neighbor, and Rain forest, were analyzed to achieve optimum classification accuracy of the received signal. Further the Performance of these classifiers compared to prove their superiority in modulation classification.

Keywords: Automatic Modulation Identification, Support vector machine, K-Nearest neighbor, Decision Tree, Rain Forest, Cognitive Radi, Adaptive radio system

1. Introduction

In a spectrum that is already fully used, Building advanced data interchange services and a successful system to serve civilian and safety purposes is difficult. Therefore, in the systems indicated above, signal processing depends on efficient algorithms. For non-ideal channels, wireless transmission at large data speeds require robust and spectrally efficient modulation techniques. To maintain adequate performance in deep fades, it is necessary to use a better coding scheme since conventional data transmission systems are unable to adapt to such channel circumstances [2]. Numerous advancements in wireless communications have been made during the past 20 years, particularly in terms of increasing through put. One such invention to provide the maximum gearbox dependability and gearbox rate through the modification is Automatic Modulation Identification.

To use Automatic Modulation Identification properly, the receiver must be notified of the method of modulation utilized to demodulates the transmitted signal. [3]. To do this, additional modulation type information is added as a file known as the header to every signal frame. As a result, receivers are alerted to any changes in modulation method and can adjust their behavior. However, the additional data has a significant impact on spectrum efficiency. To circumvent this problem, AMI is used to detect the modulation class of the received signal avoiding the requirement of overhead data. In light of this, AMI is currently critical in wireless network receivers, particularly in forthcoming adaptive radio systems (ARS) [4].

1.1 Automatic Modulation Identification (AMI)

Plenty of improvements in wireless communications have been made during the past 20 years, especially in terms of increasing throughput.

One such invention is Automatic Modulation Identification, which modifies the modulation format in connection with the channel's circumstances in order to offer the best transmission reliability and transmission rate [5]. In order to effectively carry out AMI, The receiver must be notified of the modulation scheme applied to demodulate the signal[6]. To do this, extra modulation type data is added as a file called the header to every signal frame. As a result, receivers are alerted to any changes in modulation method and are able to modify their behavior accordingly. However, the additional data has major effects on spectrum efficiency. In order to circumvent this problem, AMI is used to identify the acquired modulation of the signal type avoiding the requirement of overhead data. AMI thus becomes a vital component of Receivers for wireless communication systems, particularly for upcoming adaptive radio systems (ARSs). Various Decision Tree[7], Support Vector Machine [8], k-Nearest Neighbor, and Rain Forest classifiers are constructed and analyzed for AMI in this study.

The remainder of the essay is organized as follows: Section 2 goes through the suggested strategy's framework. Section 3 illustrates how an AMI approach using decision trees, Support Vector Machines, and K-Nearest Neighbors works[9], and Rain Forests performed in simulations with non-ideal channel circumstances.

2. SYSTEM MODEL

The general framework of the suggested method is given in Figure 1[10]. There are training and testing phases. To assess performance, a collection of modulated classes with varying noise levels is created. The learning rate parameter is applied to divide the data set into portions for training and testing.

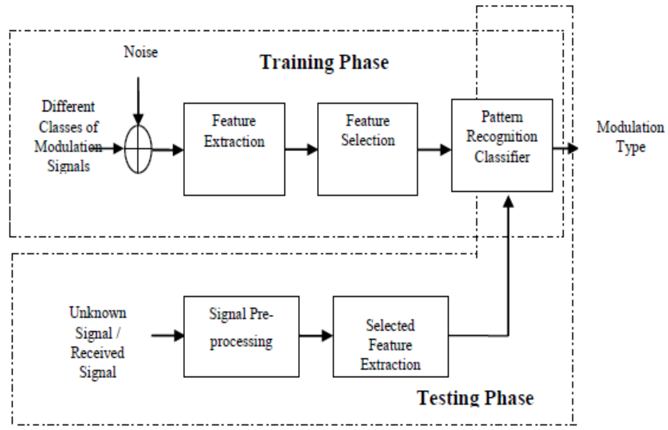

Fig1. Model of the proposed system

2.1 Signal model:

The CR receiver's input signal is represented by the expression

$$r(n) = x(n) + G(n)$$

Here, x(n) denotes the signal being sent, while G(n) denotes channel fading.The r(n) is the input binary data is[11]

$$r(n) = Ae^{i(2\pi nTf_0+\theta_n)} \sum_{k=-\infty}^{\infty} x(k)y((n-k+\epsilon)T)$$

In this scenario, A represents the amplitude, whereas x(k) represents the input of the digital stream, y(.) represents channel impacts, T is the symbol for time, n represents phase jitter, and is temporal shifts owing to channel features.

2.2 Feature extraction:

Under non-ideal channel conditions, for each set of modulated classes, several statistical characteristics are retrieved in order to train the classifier. Moments have greater values in higher order modulated signals, which makes them suitable for categorization as digital signals.

The moments for the signal that was received r(n) are retrieved as [2]:

$$M_{pq} = E[r(n)^{p-q} r^*(n)^q]$$

Here, the received signal is denoted by r(n), and its complex conjugate is r*(n), and p and q are two integers. A signal's cumulants are a collection of statistical values obtained from moments.

Moments are utilised to produce the HoC, which are then used to derive the ratios [11].

2.3 Feature selection:

Based on the analysis of the generated statistical features for every modulation categories during the stage of feature extraction, several of those moments and higher-level cumulant ratios are found to be inadequate to distinguish between modulation classes. For some of the modulation classes, the range of values for moments and higher-level ratios is the same. While increasing classification time, none of these moments or cumulant ratios improve classification accuracy. The complexity of the classifier is diminished with the use of Principle Component Analysis (PCA).

2.4 Training the classifier & testing:

During the training phase, the recommended classifiers are taught using a feature set for every reference modulated signal. Using the found attributes, four classifiers Decision Tree, Support Vector Machine, k-Nearest Neighbor, and Rain Forest are trained in this step. In the testing phase, various attributes are collected for AMC from an unidentified incoming signal after signal preprocessing. After that, the trained classifier is utilized to reorganize the modulation among the recovered attributes. Based on the model built by the machine learning algorithm during the training phase, the feature extraction set is utilized to categories an unknown signal into a certain class.

3.Pattern Recognition Classifiers:

This paper investigates the different digital modulated signals examines the various non-parametric supervised classification methods for AMI, including Decision Tree, Support vector machine, k- Nearest neighbor, and Rain forest.

3.1 Decision Trees:

Among all classifiers, DT's is the easiest to develop and uses lowest memory. The size of the tree and the level of noise affect the DTs' classification accuracy. Since binary trees make up DTs, recognition is done by moving from the root to the leaf node.

3.2 K-Nearest Neighbors:

The signal is classified under a form of modulation category in a KNN classifier based on a vote from the signal's k-nearest neighbors. A value of k, usually is chosen in accordance with the total quantity of the data set, governs how well the classifier performs.

3.3 SVM Classifiers:

Using a selection of training examples, a support vector machine (SVM), a supervised learning system, can classify noisy and high-dimension data samples.SVM categorizes the samples by locating the hyper plane that divides the data into several groups. With the suggested SVM classifiers, classification is accomplished in two phases. Using kernel functions referred to as transformations, all types of modulated signals are mapped in the first stage. The second step uses the kernel functions to separate the modulation classes in the best way possible.

3.4 Random Forest :

For Categorization & Regression problems in machine learning, the Random Forest (RF) technique is a highly well-liked supervised machine learning strategy.

4.SIMULATION RESULTS AND DISCUSSIONS:

This section evaluates the effectiveness of the proposed classifiers employing a range of modulation classes, such as BPSK, QPSK, 8-PSK, 16-QAM, 32-QAM, 64-QAM, and 128-QAM. The performance of the suggested classifiers is then evaluated using a range of SNR values under less-than-ideal channel circumstances. The effectiveness of the suggested classifiers is also evaluated in terms of how well they identify modulations. According to the simulation results, decision trees and rain forests provide classifiers that produce superior classification accuracy.

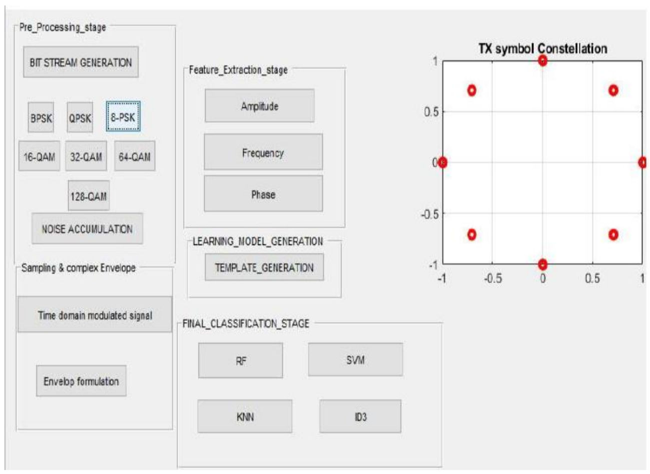

Fig 2. MATLAB GUI

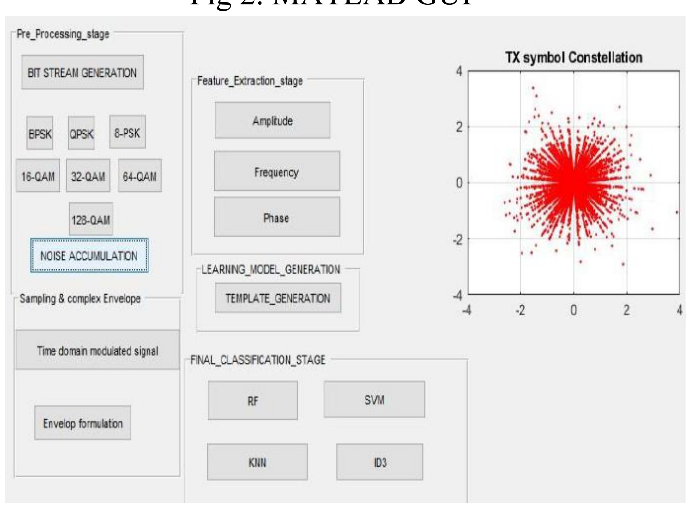

Fig 3. Noise accumulation over constellation output

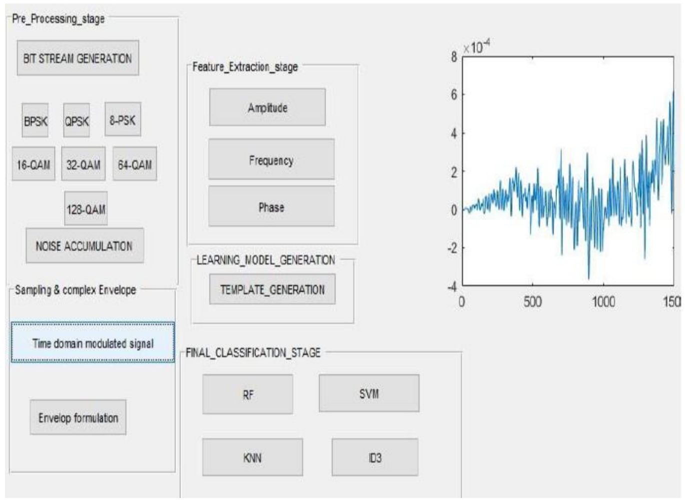

Fig 4. Time domain modulated signal

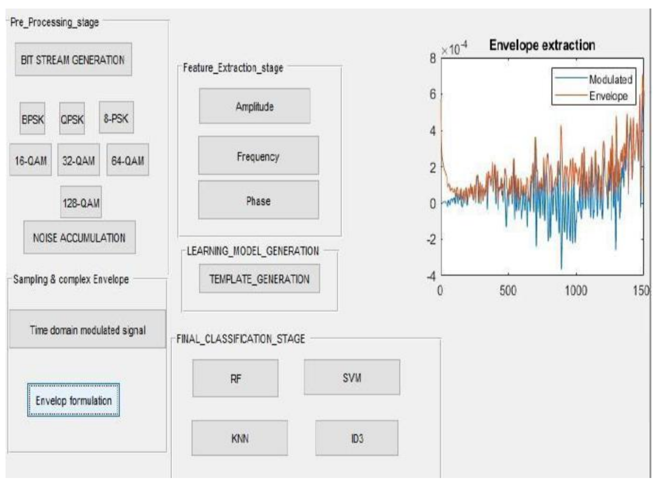

Fig 5. Time domain envelope detected signal

Fig 6. Rain forest classification report

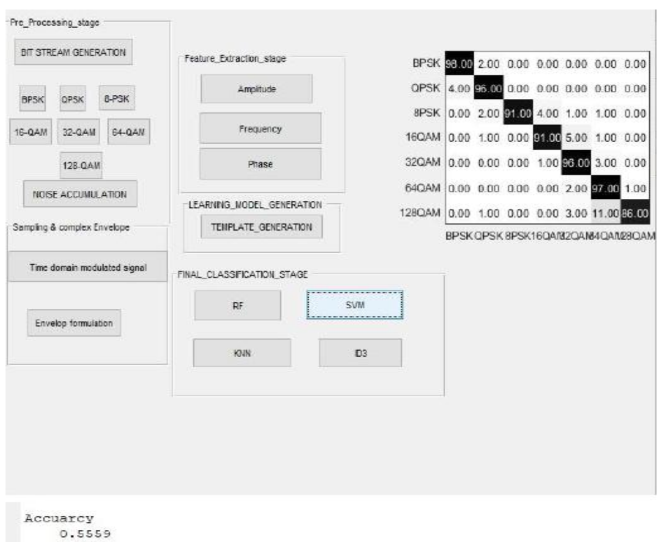

Fig 7. SVM classification report

Fig 8. KNN classification report

Fig 9. Decision Tree classification report

	Classifier	Accuracy
1	RF Algorithm	81.93
2	SVM Algorithm	55.59
3	KNN Algorithm	51.96
4	Decision tree Algorithm	83.57

Table: Performance comparison of PRC's

5.CONCLUSION

This study presents a performance analysis of the Decision Tree, Rain Forest, KNN, and SVM algorithms for recognizing blind modulation in digitally modulated signals. Even though we have additional categories of modulated signals, our classifiers' recognition accuracy is greater than that of conventional methods. Additionally, it can be seen from the simulation findings that decision tree and forest-based methods deliver superior accuracy in fading and AWGN scenarios.

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