Automatic Modulation Classification using Principle Composition Analysis based Features Selection

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***Abstract*—Automatic Modulation Classification (AMC) plays an important role in both military and civilian applications. Feature based AMC is used in this paper. Principle Component Analysis (PCA) is employed to reduce dimensions of the feature vector. Two classifiers mainly k-nearest neighbor (KNN) and Support Vector Machine (SVM) are used to investigate the correct classification rate against different SNRs for test signals. Experiments are conducted using data trained at two different SNRs of 15dB and 3dB respectively. Results show that KNN classifier shows better results when data is trained at high SNRs. However, both the classifiers show almost same performance when data is trained at low SNR.**

Keywords—Automatic Modulation Classification; Principle Component Analysis; Feature based; classifier; Support Vector Machine; k-Nearest Neighbor

I. Introduction

Automatic Modulation Classification (AMC) has been a widely researched topic. It has a significant importance in both military [1] and civilian [2] applications. In military applications, it plays a role in Electronic warfare (EW) systems that involve signal interception, jamming and identification. On the other hand, modulation classification in link adaptation [2] systems is considered extremely important for many civilian applications.

In Digital communications, transmitters modulate a data signal and receivers demodulate it to extract original information. Automatic modulation classification (AMC) is the recognition of modulation scheme at the receiver end. An automatic modulation classification (AMC) is an essential part of a multi-standard communication system as it allows blind detection of the modulation schemes present in the received signal.

Two main types of AMC approaches are likelihood based and feature based. Likelihood based classification compares a threshold with likelihood function of the received signals. Feature based classifiers exploits the distinct characteristics in extracted feature for modulation classification. Some common features found in literature are higher order statistics [3], neural networks [4], zero crossing technique [5], instantons frequency or amplitude [6] and cyclic spectrum features [7] [8]. In [9] ambiguity function domain has been used to generate distinct feature subset for modulation classification. This technique is quite effective esp. in low SNR conditions because noise is centralized in ambiguity function domain.

The aim of this paper is to investigate the performance of two machine learning based classifiers using Principle Component Analysis (PCA) algorithm. Features have been generated by taking advantage of distinct characteristics of modulated signals in ambiguity domain. The two classifiers that has been used are k-nearest neighbor and multi class Support Vector Machine (SVM).

The rest of the paper is organized as follows: Section II introduces the system model used in this paper. Section III elaborates on the feature selection algorithm that has been used. Section IV defines the designing parameter of the two classifiers. Section V concludes the paper.

II. Background and System Model

AMC using pattern recognition methods is usually not optimal but is easy to implement with close to optimal performance if designed properly. The two main components of pattern recognition based classification are feature extraction and classification. Normally classifiers performance depends on the proper design of the signal features [10]. Therefore, it is extremely important to choose feature size with maximum information. So a feature selection algorithm is used for reducing the pattern vector to a lower dimension, which comprises of the most significant information from the original vector.

The system model that has been used in this paper assumes that information is extracted from received baseband signal which is as follows:

$$r(t) = x(t) + n(t) \tag{1}$$

where r(t) is the received modulated baseband signal, x(t) depends on modulation type and n(t) is AWGN noise.

The three expressions used for $x(t)$ are as follows:

$$x_{PSK} = A\,\mathrm{Re}[\sum_{K} C_K e^{j2\pi f_c t} g(t-kT_s)] \qquad where, C_k = e^{j\frac{2\pi i}{M}} \tag{2}$$

$$x_{FSK} = A\,\mathrm{Re}[\sum_{K} e^{j2\pi(f_c+\Delta f_k)t} g(t-kT_s)] \tag{3}$$

$$x_{QAM} = A\,\mathrm{Re}[\sum_{K} C_K e^{j2\pi f_c t} g(t - kT_s)] \tag{4}$$
$$where, C_k = a_k + jb_k, a_k, b_k = 2i - M - 1$$

where s_{PSK} *=PSK modulated received sequence,* s_{FSK} *=FSK modulated received sequence,* s_{QAM} *=QAM modulated received sequence, i=0,1,2,……,M-1, A is the power of the received signal,* C_K *map the transmitted symbols,* T_s *is the symbol period,* f_c *is the carrier frequency, M is the modulation level and g(t) is the finite energy signal with a* T_s *duration.*

In this paper, three modulation types mainly MPSK, MFSK and MQAM have been used which makes up the class $I = [I_1, I_2, I_3]$.

III. Feature Selection Algorithm

In this paper, ambiguity function based frequency features at different time intervals have been used to generate a feature vector. Ambiguity function is a $M \times N$ matrix (*M* and *N* are frequency and time sizes respectively). For each class *I* distinct AF matrix is computed. Optimum features are selected as follows:

1) Connect column of AF matrix of each class to form a high dimensional vector v_H.
2) Compute Principle Component Analysis on vector v_H.
3) Sort the Eigen vectors in descending order.
4) Get 5, 10 and 20 indices of the projected matrix in new sub space according to the sorted Eigen vectors.
5) Check the classification rate with each number of indices. Indices here denotes number of features selected for classification.

The above algorithm does not require any prior knowledge of the received signal like carrier frequency. It is also robust under low SNR. Moreover, ambiguity function used in this paper have a distinct energy distributions amongst different modulation classes and thus is a good feature subset.

It can be used to classify a wider range of modulation schemes. Figure 1 and 2 shows the flowchart of the feature selection algorithm and variance of first ten principle components of the features respectively.

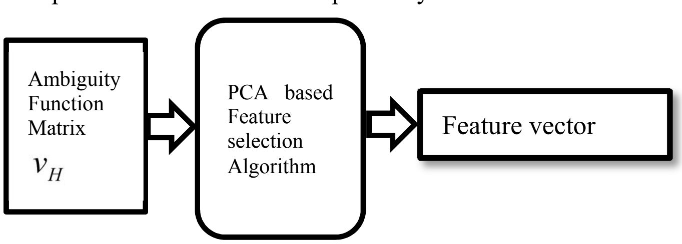

Fig. 1. Feature Selection Algorithm flowchart

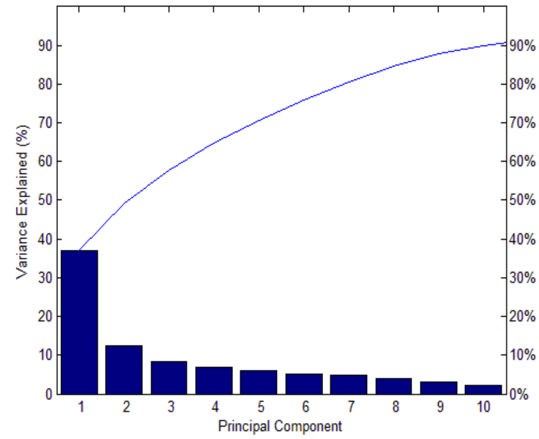

Fig. 2. Variance Vs 10 Principle Components of feature vector

IV. Classifiers

Performance of two Machine Learning (ML) based classifiers mainly: k-nearest neighbor (KNN) and Multiclass Support Vector Machine (SVM) has been investigated under different SNR values. The designing parameter for the two classifiers are as follows:

A. K-Nearest Neighbor (KNN)

KNN classifier is both simple and fast. It is designed using k nearest neighbor (k=16). Distance metric used in the designing is Euclidean. Sample are classified based on 'nearest' rule where decision is based on majority rule with nearest point tie-break.

B. Support Vector Machine (SVM)

One vs all (OVA) technique has been used for multiclass SVM. Kernel function has been modified to Gaussian radial basis function (rbf) kernel with scaling factor $\sigma = 1$. Least square ('LS') method has been used to find the separating hyperplanes.

V. Simulations and Results

TABLE I. Simulation Parameter Setting

Parameters	Signals		
	PSK	***FSK***	***QAM***
Sampling rate (kHz)	20	20	20
No. of symbols	50	50	50
Symbol period (ms)	100	100	100
Modulation order	[2,4,8,16]	[2,4,8,16]	[2,4,8,16]

The simulation parameters for the modulation schemes used have been shown in Table 1. 100 realizations of each class have been taken in training and test data formation. Each experiment is performed based on Monte Carlo simulation with n=10 trails. Test signal is generated at various SNRs ranging from -3dB to 15dB. Training data for two experiments is generated at 15dB SNR and 3dB respectively. For classification purpose, classifier is fed with train and test ratio of 60:40. Correct classification rate in percentage is chosen as the performance metric for each classifier.

Figure 3 shows the result of two classifiers with data trained at 15dB SNR. Three different features subsets with 5, 10 and 20 features have been used in the simulations. It is evident from the graph that KNN classifier shows better results than SVM classifier. SVM classifier also achieves a good performance with 5 features selected but its performance degrades with 20 features.

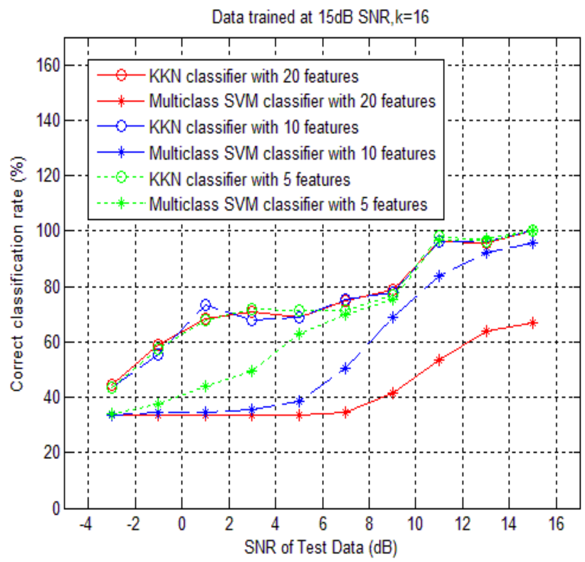

Fig. 3. Classification Rate vs different SNRs of testing data (Train data at 15dB SNR)

Figure 4 shows the classification rate for testing data at different SNRs with data trained at 3dB SNR. Features selected are only 5 and 10 in this experiment as previous results show that classifier performance with 20 features is not satisfactory. It is evident from this graph that overall performance curve of SVM based classifier is nearer to that of knn classifier. This shows that if data is trained at a noisy environment, SVM shows better results. However, still performance of knn is better than SVM with 5 and 10 features selected respectively.

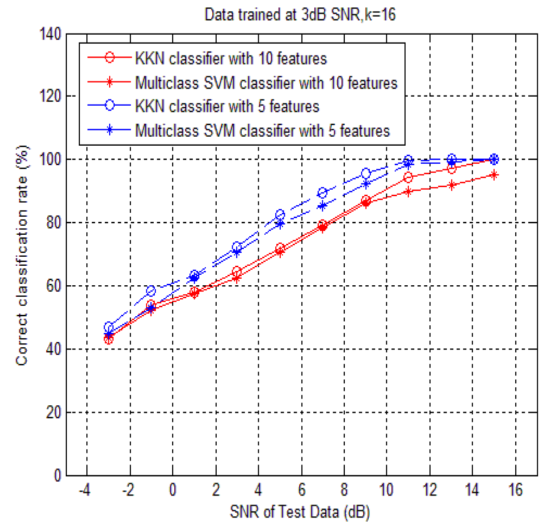

Fig. 4. Classification Rate vs different SNRs of testing data (Train data at 3dB SNR)

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