**AUTOMATIC MODULATION CLASSIFICATION USING PRINICIPLE COMPOSITION ANALYSIS BASED FEATURES SELECTION**

**ABSTRACT**

In both military and civilian applications, Automatic Modulation Classification (AMC) is crucial. In this paper, feature-based AMC is employed. A technique called Principle Component Analysis (PCA) is used to minimize the feature vector's dimensionality. To examine the accurate classification rate for test signals at various SNRs, two classifiers—primarily k-nearest neighbor (KNN) and support vector machine (SVM)—are utilized. Data trained at two distinct SNRs, 15dB and 3dB, respectively, are used in the experiments. According to the results, KNN classifier performs better when data is trained at high SNRs. However, when data is learned at low SNR, both classifiers perform nearly identically.

**Keywords:** Automatic Modulation Classification (AMC); Principle Component Analysis; Feature based; classifier; Support Vector Machine; k-Nearest Neighbor.

**LITERATURE SURVEY**

**[1] Víctor Iglesias, Jesós Grajal, Omar Yeste-Ojeda, “Automatic modulation classifier for military applications,” 19th European Signal Processing Conference, 29 Aug.-2 Sept. 2011:**

Automatic modulation recognition plays an important role in several military and civilian applications. Depending on the application, latency can be the bottleneck for designing an automatic modulation classifier (AMC). In this paper, an AMC based on low complexity signal features to improve latency and percentage of real-time operation is designed for broad-band military applications.

**Summary:** Studied about the Automatic Modulation Classifier (AMC) in military applications.

**[2] Zhechen Zhu and Asoke K. Nandi, “Modulation Classification for Civilian Applications,” Wiley, 2014:**

Automatic Modulation Classification (AMC) has been a key technology in many military, security, and civilian telecommunication applications for decades. In military and security applications, modulation often serves as another level of encryption; in modern civilian applications, multiple modulation types can be employed by a signal transmitter to control the data rate and link reliability.

This book offers comprehensive documentation of AMC models, algorithms and implementations for successful modulation recognition. It provides an invaluable theoretical and numerical comparison of AMC algorithms, as well as guidance on state-of-the-art classification designs with specific military and civilian applications in mind.

**Summary:** Studied about the Modulation Classification for Civilian Applications.

**[3] A. Swami and B. M. Sadler, “Hierarchical digital modulation classification using cumulants,” IEEE Trans. Commun., vol.48, pp. 416- 429, 2000:**

A simple method, based on elementary fourth-order cumulants, is proposed for the classification of digital modulation schemes. These statistics are natural in this setting as they characterize the shape of the distribution of the noisy baseband I and Q samples. It is shown that cumulant-based classification is particularly effective when used in a hierarchical scheme, enabling separation into subclasses at low signal-to-noise ratio with small sample size. Thus, the method can be used as a preliminary classifier if desired. Computational complexity is order N, where N is the number of complex baseband data samples. This method is robust in the presence of carrier phase and frequency offsets and can be implemented recursively. Theoretical arguments are verified via extensive simulations and comparisons with existing approaches.

**Summary:** Studied about Hierarchical digital modulation classification using cumulants.

**[4** **A. K. Nandi and E. E. Azzouz, “Modulation recognition using artificial neural networks,” Signal Processing, pp. 165-175, 1997:**

This paper presents artificial neural networks (ANNs) for the recognition of either analogue or digital modulation types. Computer simulations of different types of band-limited, modulated signals corrupted by band-limited Gaussian noise sequence have been carried out to measure the performance of the ANN approach. The threshold SNR for the recognition of either analogue or digitally modulated signals with average success rate ⩾98% is found to be about 10 dB. Comparisons of results from the ANN approaches and the decision-tree methods are presented. **Summary:** Studied about Modulation recognition using artificial neural networks.

**[5] S. Z. Hsue and S. S. Soliman, “Automatic modulation classification using zero crossing,” IEE Radar and Signal Processing, vol. 137, pp. 459-464, 1990:**

A modulation recogniser that automatically reports modulation types of constant-envelope modulated signals is developed using zero-crossing techniques. The zero-crossing sampler, as a signal conditioner, has the advantage of providing accurate phase transition information over a wide dynamic frequency range. Signal parameters such as zero-crossing variance carrier-to-noise ratio (CNR) and carrier frequency are estimated. Phase difference and zero-crossing interval histograms play the role of features for modulation recognition. The classifier performance is given in the form of a confusion matrix. The simulation results obtained demonstrate that a reasonable average probability of correct classification is achievable for CNR ages; 15 dB**.**

**SUMMARY:** Studied about Automatic modulation classification using zero crossing.

**EXISTING METHOD**

The first proposed Automatic Modulation Classification using Linear Discriminant Analysis (LDA) for extracting features that are used for classification using KNN and SVM. LDA was used for extracting features from the modulation that are used for classification using the classifiers. Later, the SVM and KNN are trained and tested feeding the same features generated by LDA. SVM and KNN showed better results at both training and testing.

Linear Discriminant Analysis or Normal Discriminant Analysis or Discriminant Function Analysis is a dimensionality reduction technique that is commonly used for supervised classification problems. It is used for modelling differences in groups i.e. separating two or more classes. It is used to project the features in higher dimension space into a lower dimension space.

For example, we have two classes and we need to separate them efficiently. Classes can have multiple features. Using only a single feature to classify them may result in some overlapping as shown in the below figure. So, we will keep on increasing the number of features for proper classification.

**KNN Classifier**

Suppose, we have an image of a creature that looks similar to cat and dog, but we want to know either it is a cat or dog. So for this identification, we can use the KNN algorithm, as it works on a similarity measure. Our KNN model will find the similar features of the new data set to the cats and dogs images and based on the most similar features it will put it in either cat or dog category.

**SVM Classifier**

SVM can be understood with the example that we have used in the KNN classifier. Suppose we see a strange cat that also has some features of dogs, so if we want a model that can accurately identify whether it is a cat or dog, so such a model can be created by using the SVM algorithm. We will first train our model with lots of images of cats and dogs so that it can learn about different features of cats and dogs, and then we test it with this strange creature. So as support vector creates a decision boundary between these two data (cat and dog) and choose extreme cases (support vectors), it will see the extreme case of cat and dog. On the basis of the support vectors, it will classify it as a cat.

**Disadvantages:**

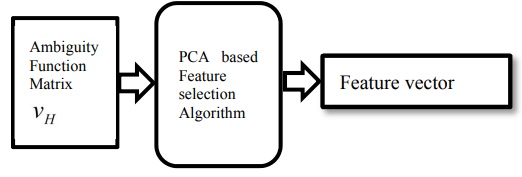
* Computationally complex.
* Outage probability will be high.

**CHAPTER 4**

**PROPOSED METHOD**

Principal component analysis, or PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. Reducing the number of variables of a data set naturally comes at the expense of accuracy, but the trick in dimensionality reduction is to trade a little accuracy for simplicity. Because smaller data sets are easier to explore and visualize and make analyzing data much easier and faster for machine learning algorithms without extraneous variables to process. In this paper, ambiguity function based frequency features at different time intervals have been used to generate a feature vector. Ambiguity function is a × NM 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: Connect column of AF matrix of each class to form a high dimensional vector Hv. Compute Principle Component Analysis on vector Hv. Sort the Eigen vectors in descending order. Get 5, 10 and 20 indices of the projected matrix in new sub space according to the sorted Eigen vectors. 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.

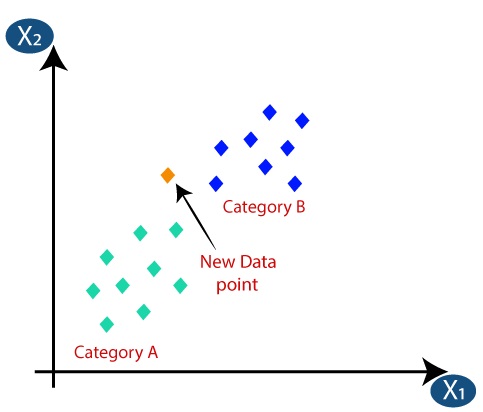


**KNN Classifier**

Suppose there are two categories, i.e., Category A and Category B, and we have a new data point x1, so this data point will lie in which of these categories. To solve this type of problem, we need a K-NN algorithm. With the help of K-NN, we can easily identify the category or class of a particular dataset.

The K-NN working can be explained on the basis of the below algorithm:

1. Select the number K of the neighbors
2. Calculate the Euclidean distance of K number of neighbors
3. Take the K nearest neighbors as per the calculated Euclidean distance.
4. Among these k neighbors, count the number of the data points in each category.
5. Assign the new data points to that category for which the number of the neighbor is maximum.
6. Our model is ready.



1. Firstly, we will choose the number of neighbors, so we will choose the k=5.
2. Next, we will calculate the Euclidean distance between the data points. The Euclidean distance is the distance between two points, which we have already studied in geometry. It can be calculated as:
3. By calculating the Euclidean distance we got the nearest neighbors, as three nearest neighbors in category A and two nearest neighbors in category B.
4. As we can see the 3 nearest neighbors are from category A, hence this new data point must belong to category A.

Here, in this paper the feature vector generated by the Principal Composition Analysis (PCA) is fed to the KNN classifier. The classifier is trained on the features generated by PCA. The Classifier trained on the less but more accurate features which were generated in the previous stage. The KNN classifier takes more time to train, if the feature vector is large and have more features. So, the PCA is more efficient at achieving this particular thing. The training data will be both 3dB and 15dB respectively. The KNN classifier is trained on both for achieving a greater accuracy. The classifier is tested using the test data that were separated during the initial stage. KNN classifier is better at classifying the data at lower dBs but at higher dBs both classifiers showed almost similar results.

Here, in this paper, we are training the Support Vector Machine (SVM) with the features generated by PCA at both 3dB as well as 10dBs. The feature vector consists of less but very accurate features for a better training. The training is most complex process during the artificial intelligence environment. The training will take from minutes to as long as days. So, a feature vector of less size with an accurate details extraction is much more important. Here, the PCA is better at achieving the particular thing. Later, the classifier is tested using the test data that were separated at the initial stage. The SVM showed almost similar results at higher dBs as KNN classifier.

**CHAPTER 5**

**ADVANTAGES AND APPLICATIONS**

**Advantages:**

* The advantage of Principle Composition Analysis (PCA) is its feature vector which has less size compared to any other existing techniques.
* The PCA’s feature vector makes the training process consumes less time compared to existing techniques.
* KNN classifier as well as SVM classifier takes less time for a better training.

**Applications:**

* Machine Learning
* Deep Learning
* Digital Signal Processing
* Medical Signal Processing

**Software & Hardware Requirements:**

**Software:** Matlab 2020a or above

**Hardware:**

**Operating Systems:**

* Windows 10
* Windows 7 Service Pack 1
* Windows Server 2019
* Windows Server 2016

**Processors:**

Minimum: Any Intel or AMD x86-64 processor

Recommended: Any Intel or AMD x86-64 processor with four logical cores and AVX2 instruction set support

**Disk:**

Minimum: 2.9 GB of HDD space for MATLAB only, 5-8 GB for a typical installation

Recommended: An SSD is recommended A full installation of all MathWorks products may take up to 29 GB of disk space

**RAM:**

Minimum: 4 GB

Recommended: 8 GB

**Learning outcomes:**

* Introduction to Matlab
* What is EISPACK & LINPACK
* How to start with MATLAB
* About Matlab language
* Matlab coding skills
* About tools & libraries
* Application Program Interface in Matlab
* About Matlab desktop
* How to use Matlab editor to create M-Files
* Features of Matlab
* Basics on Matlab
* What is an Image/pixel?
* About image formats
* Introduction to Image Processing
* How digital image is formed
* Importing the image via image acquisition tools
* Analyzing and manipulation of image.
* Phases of image processing:
* Acquisition
* Image enhancement
* Image restoration
* Color image processing
* Image compression
* Morphological processing
* Segmentation etc.,
* How to extend our work to another real time applications
* Project development Skills
  + Problem analyzing skills
  + Problem solving skills
  + Creativity and imaginary skills
  + Programming skills
  + Deployment
  + Testing skills
  + Debugging skills
  + Project presentation skills
  + Thesis writing skills