Design of Modulation Classification Algorithm in Non-Ideal Channel conditions

M.KiranKumar[@] and Dr.G. Sudhakar[*]
@ B.Tech, Dept. of ECE, Santhiram Engineering College, Nandyal
* Lecturer, Dept. of Physics, Govt Degree College for Men, Kurnool

Abstract:

The classification of digital modulation schemes plays an important role in communication intelligence (COMINT) and other related applications. The existing algorithms for modulation classification consider a semi-blind scenario, where certain signal parameters are assumed to be known. The pre-processing accuracy of signal parameters like the symbol rate, the center frequency, the carrier phase and the signal amplitude etc., has direct implication on classification. Here we address the case of model mismatch due to the amplitude un-certainty in maximum likelihood (ML) classification and propose a new approach to mitigate the situation. The method is based on the normalization of received signal amplitude using fuzzy clustering algorithm. Simulation results are presented to show the robustness of the algorithm for blind scenario.

Keywords: Modulation Classification(MC), Maximum Likelihood(ML), Log Likelihood Function, Quadrature Amplitude Modulation(QAM), Fuzzy C-means Algorithm.

Introduction:

In a world of rapid growth of commercial wireless services, accommodating the explosive demand for spectrum access, efficiency and reliability becomes increasingly technically challenging. furthermore, implementation of advanced information services for military applications in a crowded electromagnetic spectrum is a challenging task for communication engineers. A solution is provided by flexible intelligent radios, capable of sensing and adapting to the environment. In such radios, modulation classification (MC) is an important task. A modulation classifier essentially involves two steps: signal preprocessing and application of a classification algorithm. Signal preprocessing tasks may include estimation of signal amplitude and phase, and noise power, symbol timing and waveform recovery, etc.

Modulation classification is the process of recognizing the modulation type of received signal. Modulation classifier will not have much information about signal emitter; even it is invisible to signal emitter and is used to pick up some useful information for either military or civic applications. In military these are employed for electronic surveillance, interference identification etc.

Need of Modulation Classification:

Modulation classification plays a important role in COMINT(communication intelligence). Historically, COMINT systems have dependent on the manual modulation recognition of measured parameter in order to provide classification of different emitters. But recently automatic recognition systems have come into picture.

Most of veiled and manifest operations of classification of modulation whether of analog or digital modulation technique are performed because it is necessary to know the type of incoming signal. How to observe and identify modulated signals is necessary to know about valuable information. The recognizers help to differentiate the signal in presence of (AWGN) along with presence of other signals the process of recognition is a most important intermediate step between the detecting and demodulating process.

One of historic models of modulation recognizers make use of bank of demodulators each of them is designed for single type of modulation, by observing the demodulation output one can decide the modulation type of received signal. This requires highly skilled operators. Automatic recognizers are performed by using a set of intelligent decision algorithm at demodulation output.

Fuzzy Clustering Means (FCM) Algorithm:

Normalization requires to estimate the constellation points using a clustering algorithm. Among the available clustering algorithms, the fuzzy-c means (FCM) clustering algorithm is chosen due to it's advantage over K-means algorithm in terms of the convergence accuracy.

Explanation of clustering:

Data clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used, different measures of similarity may be used to place items into classes, where the similarity measure controls how the clusters are formed. Some examples of measures that can be used as in clustering include distance, connectivity, and intensity.

In hard clustering, data is divided into distinct clusters, where each data element belongs to exactly one cluster. In **fuzzy clustering** (also referred to as **soft clustering**), data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data element and a particular cluster. Fuzzy clustering is a process of assigning these membership levels, and then using them to assign data elements to one or more clusters.

In fuzzy clustering, every point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster. Thus, points on the edge of a cluster, may be in the cluster to a lesser degree than points in the center of cluster. An overview and comparison of different fuzzy clustering algorithms is available.

Any point x has a set of coefficients giving the degree of being in the kth cluster $wk(x)$. With fuzzy c-means, the centroid of a cluster is the mean of all points, weighted by their degree of belonging to the cluster.

$$c_k = \frac{\sum_x w_k(x)^m x}{\sum_x w_k(x)^m}.$$

The degree of belonging, $wk(x)$, is related inversely to the distance from x to the cluster center as calculated on the previous pass. It also depends on a parameter m that controls how much weight is given to the closest center. The fuzzy c-means algorithm is very similar to the k-means algorithm.

Algorithmic steps for Fuzzy c-means clustering:

Let X = {x1, x2, x3 ..., xn} be the set of data points and V = {v1, v2, v3 ..., vc} be the set of centers.

1) Randomly select *'c'* cluster centers.
2) Calculate the fuzzy membership *'µij'* using:

$$\mu_{ij} = 1 / \sum_{k=1}^{c} (d_{ij} / d_{ik})^{(2/m-1)}$$

3) Compute the fuzzy centers *'vj'* using:

$$v_j = (\sum_{i=1}^{n} (\mu_{ij})^m x_i) / (\sum_{i=1}^{n} (\mu_{ij})^m), \forall j = 1, 2, ...c$$

4) Repeat step 2) and 3) until the minimum *'J'* value is achieved or $||U(k+1) - U(k)|| < \beta$.

where,

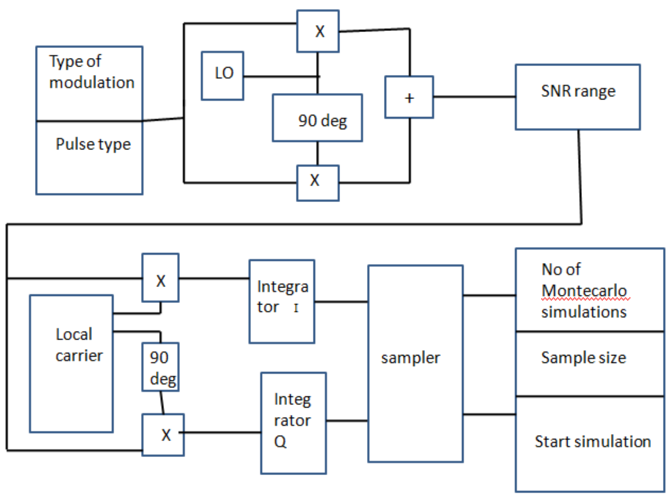
'k' is the iteration step.

'β' is the termination criterion between [0, 1].

*'U = (µij)n*c'* is the fuzzy membership matrix.

'J' is the objective function.

The block diagram shown below is designed using matlab GUI to know the experimental results as waveforms.



Experimental Results and Discussions:

The performance of the modulation classifier is measured by plotting probability of correct classification averaged over all the candidate modulation schemes over a range of signal to noise ratios. As the analytical solution involves successive integrations, Monte Carlo simulation is convenient to plot the performance of the classifier. For experimental evaluation, the probability *PD* of correct classification is defined by

$$P_D = \frac{N_C}{N_T},$$

Where,

NC and *NT* are number of correct decisions and total number of experiments respectively.

As $NT \rightarrow \infty$, PD will approach the analytical value. However, by keeping NT sufficiently large, the results can still be approximated to the analytical value.

First we plot the performance of the likelihood based classifier with amplitude model mismatch. Monte Carlo simulation with 1000 iterations and 100 sample points is considered. Fig shows the plot with a various degree of amplitude mismatch. The gradual degradation of classifier performance is evident in the figure.

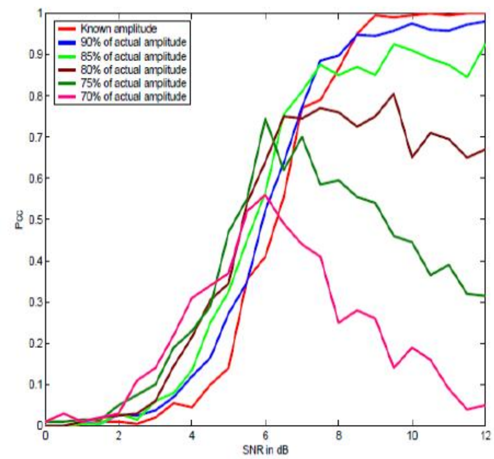


Fig :comparative performance of MC with accurate and erroneous amplitude scaling

Conclusion:

In this paper we have considered the case of amplitude uncertainty as one of the preprocessing issues and proposed a method to mitigate the same. Future focus is to improve the amplitude normalization algorithm for better classification performance in low SNR conditions. Further, the number of candidate modulations needs to be increased to include all possible digital modulation schemes currently in use.

References:

[1] Gaurav Jyothi Phukan, P.K. Bora , A.Rajesh and Chaveli Ramesh, " Amplitude Normalization in Blind Modulation Classification", in Communications(NCC).

[2] Y. Yang, C. H. Liu, and T. W. Soong, "A log-likelihood function-based algorithm for QAM signal classification," *Elsevier Signal Processing*, vol. 70, pp. 61–71, 1998.

[3] A. Puengnim, N. Thomas, J. Y. Tourneret, and JosepVidal, "Classification of linear and non-linear modulations using the Baum Welch algorithm and MCMC methods," *Elsevier Signal Processing*, vol. 90, pp. 3242–3255, 2010.

[4] P. Panagiotou, A. Anastasopoulos, and A. Polydoros, "Likelihood ratio tests for modulation classification," in *Proc.IEEE Veh. Technol. Conf.*, vol. 2, Los Angeles, CA, October 2000, pp. 670–674.

