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Adaptive modulation recognition based on the evolutionary algorithms

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ABSTRACT

Nowadays, the development of classification algorithms gives the ability to improve Automatic Modulation Recognition (AMR) effectively. This paper presents a novel modulation recognition algorithm based on clustering approach. Generally, we aim to distinguish multicarrier modulation OFDM from single-carrier modulations. In this regard, two statistics of the amplitude of the received signal are calculated at the output of a quadrature mixer as key features. The extracted features of training data points are submitted to the clustering algorithm, then, centroids for single-carrier and multicarrier modulations are assessed. Afterwards, each point of testing dataset is dedicated to its nearest centroid based on Euclidian distance and the recognition is accomplished. Simulation results demonstrate that the algorithm is beneficial in a wide range from low to high SNRs.

1. Introduction

For any communication signal analysis, knowing the modulation type is an important subject. Thus, automatic modulation recognition has gotten a major importance in different communication systems such as software defined radios, cognitive radios and military communication systems for various purposes including spectrum monitoring and adaptive communication. Basically, available Automatic Modulation Recognition (AMR) algorithms can be categorized into two main approaches [1]: (1) Feature-Based method (FB) and (2) Likelihood-Based algorithm (LB). FB methods classify the received signals based on extracted parameters called key features. These features can be derived from instantaneous information, higher order statistics, spectrum features, and etc. Although this technique leads to a suboptimum solution, it decreases the computational complexity. With regard to two distinct part of FB algorithms i.e., feature extraction and classifier, several investigations have been conducted in this area [2]. In [3], a genetic algorithm selects a suitable combination of higher order cumulants and higher order moments as key features and a hierarchical support vector machine is proposed as classifier. Ebrahimzadeh et al. proposed higher order statistics as features and hybrid radial basis function neural network (classifier) and particle swarm optimization in [4]. In [5], authors proposed an investigation on two classifiers, i.e., neural network and support vector machine in AMR. These algorithms have high percentage of correct classification to distinguish different types of digital signal even at low SNRs. As it is evident, in LB algorithms, probabilistic and hypothesis arguments are utilized to solve the modulation recognition problem [6–9]. The LB algorithms attempt to minimize the probability of misclassification and attain optimal solution. In despite of giving the optimal solution, the LB approaches suffer from several disadvantages. Owing to analytical difficulties, computational complexity is imposed on the implementation of such algorithms. In contrast to LB method, easy implementation and lower complexity of FB techniques made these methods more popular.

The recent trends have shown a growth of multicarrier modulation utilization in various applications including DVB, WLAN, WMAN and etc. This issue necessitates researchers to introduce novel algorithms for distinguishing multicarrier (MC) modulations from single-carrier (SC) ones. For instance, in [10], a detector based on fourth-order cumulants is proposed which employs the Gaussian characteristic of Orthogonal Frequency-Division Multiplexing (OFDM) in the time domain. In this method, the statistical test of Giannakis and Tsatsanis is adapted to the modulation recognition algorithm. However, this technique faces problem

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when the number of subcarriers is low and also lacks robustness to the model mismatch such as channel effect. Then, Li et al. applied a Gaussianity test based on empirical distribution function (EDF) to identify OFDM from SC modulations in [11]. These two algorithms are too complex and suffer from computational complexity. In [12], the authors have presented a moments-based algorithm in High Frequency (HF) "poor path" channel which uses the ratio of higher order moments to eliminate the multipath effect. Although the method is easy to implement and is able to take the effects of channel into consideration, the probability of detection decreases in low Signal-to-Noise Ratio (SNR). Wavelet transform is another approach in OFDM recognition which is implemented in [13,14]. Despite the fact that the correct identification rate of OFDM versus SC reaches 100% in multipath Rayleigh fading channel and when SNR = 0 dB, there is a limitation on symbol rate [14]. Zhu et al. have introduced energy distribution parameters as spectrum-based features for OFDM discrimination [15]. However, this method is not efficient and reliable at low SNRs. In [16], the distinction of ambiguity function (AF) images of different modulation signals leads to presentation of a novel algorithm. In this algorithm, low dimensional vector based on the principal component analysis (PCA) and invariant moment of AF images are submitted to Support Vector Machine (SVM) classifier as key features. This method suffers from computational complexity, although it achieved the desired results in negative SNRs. Ulovec utilizes the statistics of the signal at the output of the intermediate-frequency stage for recognizer in [17,18].

Despite the fact that many algorithms have been suggested to distinguish OFDM from SC modulations but no reliable solution which can guarantee the optimal solution has been found. Consequently, this paper aims to introduce a new modulation recognition algorithm which benefits from supervised learning technique. Actually, this method makes use of labeled dataset for training the system. The training data points tend to form discrete clusters such that members in one cluster share high degree of likeness. On the other hand, the data in one cluster should be dissimilar to the data from other cluster. In this regard, centroids for each cluster are found based on our proposed modified *K*-means algorithm. The modification consists of four famous optimization algorithms named: Teaching-Learning-Based Optimization (TLBO), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Gravitational Search Algorithm (GSA). It should be note that TLBO comprises two phases and consequently the system has five sub-modification methods. In the iterations, one of the sub-modification methods is chosen based on a calculated probability and the roulette wheel mechanism. Finally, any unlabeled data can be dedicated to its nearest cluster center. The key features are calculated based on the signal amplitude in presence of additive white Gaussian noise. In this paper, we introduce two different procedures to recognize input data modulation. In the first technique, the algorithm needs no prior information and estimation about the incoming radio signal except the training procedure. Instead, the second method utilizes a SNR estimator to complete the classification.

The remaining of the paper can be categorized as follows. Section 2 describes extraction procedure of the key features. In Section 3, the *K*-means clustering approach and modified algorithm are introduced, respectively. Section 4 gives a step-wise description on the application of modified clustering method in modulation recognition. Section 5 depicts the adaptive *K*-means algorithm for adjustment of centers by input dataset. There would be a discussion on the complexity of our proposed method in Section 6. In Section 7, the simulation results illustrate the feasibility of the proposed method and some comparisons are performed. A summary and conclusion on suggested algorithm is presented in Section 8.

2. Parameter extraction

The proposed algorithm can be separated into two distinct parts: (1) feature extraction part and (2) recognition subsystem. The first subsystem has an obligation to extract key features from received signal. In this section, it is desired to introduce the system model and feature extraction procedure. If we assume $S_r(t)$ and $S_m(t)$ as received and modulated signals, a detailed description of sampled radio-frequency signal can be expressed as below [17]:

$$S_r[k] = \frac{S_m[k]}{\sqrt{\frac{1}{N_f}\sum_{k=0}^{N_f}(S_m[k])^2}} + n[k] \quad k = 0, \ldots, N_f - 1 \tag{1}$$

where N_f is the number of samples with sampling frequency f_s, and $S_m[k]$ stands for sampled modulated signal with central frequency f_c. Due to the normalization of the $S_m[k]$ to its power, the standard deviation of the useful signal is equal to 1. Other than that, an additive white Gaussian noise is considered to declare channel effect. If B displays the system bandwidth, $n[k]$ can be expressed as a normal distributed vector with zero-mean and variance σ_n^2 given by:

$$\sigma_n^2 = \frac{f_s}{2B}\frac{1}{10^{\frac{SNR}{10}}} \tag{2}$$

where SNR is Signal-to-Noise Ratio. Two channels of quadrature and in-phase are considered and two signals are produced at the output of inter-mediate (IM) quadrature mixer with frequency of f_{IF}, where IF refers to Inter-mediate Frequency.

$$r'_Q[k] = \cos\left(2\pi\frac{f_o}{f_s}k\right) S_r[k] \quad k = 0, \ldots, N_f - 1 \tag{3}$$

$$r'_I[k] = \sin\left(2\pi\frac{f_o}{f_s}k\right) S_r[k] \quad k = 0, \ldots, N_f - 1 \tag{4}$$

where f_o represents the local oscillator frequency ($f_o = f_{IF} + f_c$). In order to prevent the presence of useless products of mixing, a Finite Impulse Response (FIR) filter is implemented with bandwidth equal to $2f_{IF}$ [18]. After FIR filtering, $r'_Q[k]$ and $r'_I[k]$ are decimated by factor two and formed $r_Q[k']$ and $r_I[k']$. The amplitude of the received signal is calculated as follows:

$$S_A[k'] = \sqrt{(r_Q[k'])^2 + (r_I[k'])^2} \quad k' = 1, \ldots, N_f/2 \tag{5}$$

Without loss of generality, we can assume N_f is an even integer number. Afterwards, the amplitude signal is normalized to its power.

$$S_{An}[k'] = \frac{S_A[k']}{std\left\{S_A[k']\right\}} \quad k' = 1, \ldots, N_f/2 \tag{6}$$

In the above expression, index n corresponds to normalization and *std* stands for standard deviation of the signal. The first key feature is assessed based on following formulation:

$$\mu_4 = \frac{2}{N_f}\sum_{k'=1}^{N_f/2}(S_{An}[k'])^4 \tag{7}$$

It is evident that μ_4 shows the Kurtosis of the normalized amplitude signal. Actually, Kurtosis, as a high-order statistic, measures the deviation of a distribution from the normal distribution. As a consequence of normal distribution of the amplitude of OFDM, it can be beneficial to use Kurtosis as a key feature to distinguish MC modulations. Another key is the amplitude that can