Automatic Modulation Recognition Using Support Vector Machines Based on Higher Order Cumulants

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Abstract-- In radio communications, the need for recognizing the modulation type of the signals is increasing for its main role in the radio monitoring stations specifically for the electronic warfare field. This paper focuses on classifying some types of modulations, namely BPSK, QPSK, CPFSK, 4PAM and AM-DSB using support vector machines (SVMs) algorithm based on the high order cumulants (HOC). The two main phases of this classification approach are feature extraction and classifier training and testing. The feature extraction is carried out based on high order cumulants. Those features are the first, the second, the fourth and the sixth order moments. Using this extracted set of features a feature vector is constructed for each signal and a radial basis function support vector machine (RBF-SVM) algorithm is trained and its hyper-parameters are tuned to get the best of its performance. The results show a high accuracy of classification among the test signals under different values of signal-to-noise ratio (SNR) down to -20 dB.

Keywords—Automatic Modulation Recognition, high-order cumulant, Support Vector Machine (SVM), Radial Basis Function (RBF) Kernel.

I. Introduction

Automatic recognition of radio communication signals has widespread applications in communication field; some of those applications are electronic warfare, radio spectrum management, threat analysis and electronic surveillance.

The recognition of the transmitting signal is very difficult in the non-cooperative environments because in this case there is no prior knowledge about the signal features. All radio systems must use a modulation type; this is why the modulation type recognition is the most significant sorting parameter of the communication signal. Therefore, the recognition of the signal modulation type makes it possible to identify and track.

The modulation recognition is to determine the modulation type without any prior knowledge about the signal. There are two approaches to signal modulation recognition: automatic and non-automatic. We are concerned about the automatic modulation recognition in which the human does not involve, and that is why it has fast response compared to the non-automatic modulation recognition, where the process success needs expertise operator [3].

The modulation recognition is an intermediate step between signal interception and information recovery, which automatically identifies the modulation type of the received signals for next tasks such as demodulation. Automatic modulation recognition (AMR) of digitally modulated signals consists of two groups: inter-class and intra-class. If the signals to be recognized are of the same modulation class like phase shift keying (PSK), frequency shift keying (FSK) and amplitude shift keying (ASK) then its inter-class AMR. In addition, for intra-class AMR the signals are of the same class as BPSK and QPSK. In this paper, we do the intra-class and intr-class AMR [3] [1].

To recognize the modulation type there exist various methods and algorithms and many other methods for extracting features representing the signal characteristics in different situations [1] [3].

A. K. Nandi and E. E. Azzouz have proposed robust features under any conditions and also automatic modulation recognition algorithms based on decision tree and artificial neural networks (ANN) [1] [2].

ANN includes many approaches such as Multi-layer perceptrons (MLP) [2], radial basis function (RBF) networks, and support vector machines (SVMs) [4]. The MLP model has a critical drawback that the training procedure often gets stuck at a local optimum of the cost function, but it has a wide use for its simple implementation. The RBF model avoids the problem of local optima [3].

We concern about the pattern recognition (PR) methods using SVMs for their robustness and easy implementation [4] [1]. In PR methods, the modulation classification modules are usually composed of two stages. The first is a key feature extraction stage, which extracts the key features from the incoming signal. The second stage of PR is the classifier, which determines the modulation type of the signal based on the input features vector. There are also various classifiers used for modulation recognition, such as support vector machines (SVM) classifiers, decision-tree classifiers and neural network classifiers. The purpose of the paper is to demonstrate the possibility of recognizing modulation signal type at signal-to noise ratio (SNR) values down to -20 dB normally by the use of SVM classifier. The SVM classifier implementation is carried out using python programming language. It works in two stages the first is training and tuning the classifier hyper-parameters and the second is the test and validation.

The overall recognizer can be clearly shown in Fig.1

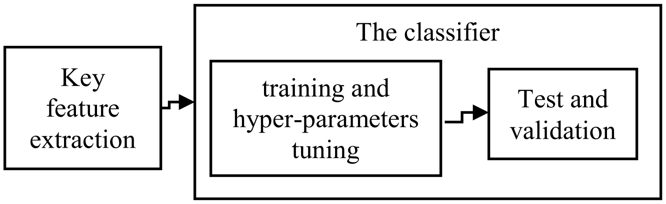

Fig. 1 Automatic Modulation Recognition stages

where the input is the intercepted signal and the output is the modulation type of that signal.

The paper is organized as follows. Section 2 provides the signals and the HOS features for classification. In Section 3, the modulation classification using SVM is presented. then we investigate the performance of the SVM classifier
, and in Section 4, the paper is concluded.

II. SIGNALS AND KEY FEATURES

A. *signals*

The modulation is carried out using an analogue carrier signal, which is usually modulated by a binary message code, and this process can be done by varying the carrier amplitude, frequency, or phase, or a combination of them. In amplitude shift keying (ASK): the carrier amplitude changes. While the carrier frequency changes in frequency shift keying (FSK). The carrier phase varies in according to the signal in the phase shift keying (PSK). If a combination of PSK and ASK is done it is called QAM. There exist Lower- and higher-order modulation schemes for each type, such as binary frequency shift keying (BFSK)[2][3].

The implemented classifier is trained to classify five types of modulations, and they are binary phase shift keying (BPSK), Quadrature phase shift keying (QPSK), continuous phase frequency shift keying (CPFSK), pulse amplitude modulation (4PAM) and amplitude modulation (AM-DSB) which comprises both inter- and intra-classes of modulation recognition.

The signals that are used as a data in the training phase and the testing phase are corrupted with an additive white Gaussian noise at different values of SNR from -20 to 18 dB. Then the data is split into two sets the training and testing sets.

The generated signals have different modulating signal, according to the sampling theory of the band-limited signals.

B. *key features*

For the recognition of the modulation type a four different order HOS are selected that have robust properties sensitive to modulation types and insensitive to variation in SNR of the signal. the selected features have a great performance against interference. The best ways to extract such features is to use information contained in the incoming signal instantaneous amplitude, phase and frequency.

The fourth-order cumulants proved its stable performance under different conditions for classifying the different classes of the phase shift keying modulation. In later research[7], the performance of classification based on the sixth-order cumulants is proved to get enhanced and improved. Thus In this paper, the classification is made based on the first order cumulants, the second-order cumulants, the fourth-order cumulants and the sixth-order cumulants. Moreover, they are defined as follows:

For a zero-mean complex stationary random process X (t), the k-order cumulant is defined as[6] :

$$C_{kx}(f_1, f_2, \ldots, f_{k-1}) = \mathrm{Cum}(\mathrm{X(t)}, \mathrm{X}(\mathrm{t}+f_1), \ldots, \mathrm{X}(\mathrm{t}+f_{k-1})) \quad (1)$$

Where :

Cum (.) is the solution of the cumulant.

X (t) the order mixing moment of the random process and expressed as $M_{pq} = E\{[x(t)^{p-q} x^*(t)^q]\}$

1) The first-order cumulants

The first-order moment can be defined in two different ways depending on placement of conjugation

$$C_{10} = M_{10} \quad (2)$$
$$C_{11} = M_{11} \quad (3)$$

2) The second-order cumulants

Similary the second-order cumulants can be written in three different ways as follows [7] [5] :

$$C_{20} = \mathrm{Cum}(\mathrm{X};\ \mathrm{X}) = M_{20} \quad (4)$$
$$C_{21} = \mathrm{Cum}(\mathrm{X};\ X^*) = M_{21} \quad (5)$$
$$C_{22} = \mathrm{Cum}(X^*;\ X^*) = M_{22} \quad (6)$$

3) The fourth-order cumulants

The fourth-order moment can be defined as follows [7][6] :

$$C_{40} = \mathrm{Cum}(\mathrm{X,X,X,X}) = M_{40} - 3{M_{20}}^2 \quad (7)$$
$$C_{41} = \mathrm{Cum}(\mathrm{X,X,X},X^*) = M_{41} - 3M_{20}M_{21} \quad (8)$$
$$C_{42} = \mathrm{Cum}(\mathrm{X,X},X^*,X^*) = M_{42} - |M_{20}|^2 - 2{M_{21}}^2 \quad (9)$$

4) The sixth-order cumulants

It is found as similar to the previous cumulants such that [7]

$$C_{60} = M_{60} - 15M_{40}M_{20} + 30{M_{20}}^3 \quad (10)$$
$$C_{61} = M_{61} - 5M_{21}M_{40} - 10M_{20}M_{41} + 30M_{21}{M_{20}}^2 \quad (11)$$
$$C_{62} = M_{62} - 6M_{42}M_{20} - 8M_{41}M_{21} - M_{40}M_{20} + 6M_{22}{M_{20}}^2 + 24{M_{21}}^2M_{20} \quad (12)$$
$$C_{63} = M_{63} - 6M_{41}M_{20} - 9M_{42}M_{21} + 18M_{21}{M_{20}}^2 + 12{M_{21}}^3 \quad (13)$$

III. SUPPORT VECTOR MACHINES (SVM)

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. They use machine learning theory to maximize predictive accuracy while avoiding over-fit to the data. Support Vector machines systems use hypothesis space of a linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. SVM became widely known because of its success in many applications such as hand-written digit recognition. SVM is chosen for its excellent generalization properties, Complexity of the classifier is characterized by the number of support vectors not the transformed space dimension and the kernel functions when dealing non linearly separable data [4].

A. *support vector machines*

The SVM works first, to maximize the margin between the two nearest data points that belong to different classes, then, it makes sure that all data points belong to the right class that is why we got to solve an optimization problem using the Lagrange multipliers [4].

In case of non-separable data based on Cover's Theorem, SVM maps the training data nonlinearly into a higher-dimensional feature space whch, make it more likely to be linearly Separable through a kernel function, and constructs a separating hyperplane with maximum margin. this mapping is a kernel function transforms the data into a higher dimensional feature space to make it possible to perform linear separation on the data. No need to perform this mapping explicitly, because we use the dot product of feature vectors in both the training and test. There are many kernel functions that can be applied such as the linear, radial basis function and polynomial.in our study we apply a radial basis function [4].

Radial Basis Function Kernel (RBF)(Gaussian) is defined mathematically as in $K(x,y) = \exp(-\gamma\|x - y\|^2)$ (14)

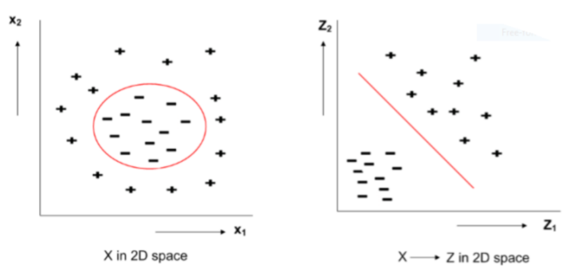

Fig.2 mapping to higher dimension to make linear separation of data

As we apply the kernel function, we save a lot of computational power that we do not need to transform the data into higher dimensional space, On the other hand, Traditional classification approaches perform poorly when working directly because of the high dimensionality of the data, but Support Vector Machines can avoid the pitfalls of very high dimensional representations. A hyper-parameter called 'C' is introduced to SVM which allows to control the trade-off between:

(1) A wide Margin

(2) Correctly classify the training data

'C 'is a non-negative "Tuning" parameter. If C=0, implies that no violation of the margin is possible.for small 'C' : we have Large Margin, Less violation on training data, Low training error, less bias, Fewer support vectors and Higher variance.

B. *SVM training and hyper-parameter search*

The input to the SVM classifier is the four key features that were extracted in the first stage. A total of 80000 modulated signals were generated and then divided into two distinct sets the first is the training set which comprises 80 percent of the signals , and the second is the test set with the remaining 20 percents of the signals . As SVM has some hyper-parameters (C and gamma values) and finding optimal hyper-parameter is a very hard task to solve. But it can be found by just trying all combinations and see what parameters work best. The main idea behind it is to create a grid of hyper-parameters and just try all of their combinations. The hyper-parameters search is carried out using the GridSearchCV python function in the Scikit-learn module. then the best classifier with the higher score is saved and used for further testing and validation. The best classifier is found to have the hyper-parameters C=1, gamma=0.1 and an rbf kernel.

C. *SVM testing*

The test data set (20 percent of the all signals) is used to test the trained classifier and its ability to generalize. Those test had never been seen before by the trained classifier. The classifier predicts a classification of the input signal based on the previous training.

IV. RESULTS

The results of the performance evaluation of the RBF- SVM for recognizing five types of signals (BPSK, QPSK, CPFSK, 4PAM and AM-DSB) based on many realizations for each modulation type at different SNR Values are displayed in the confusion matrix in fig.3.

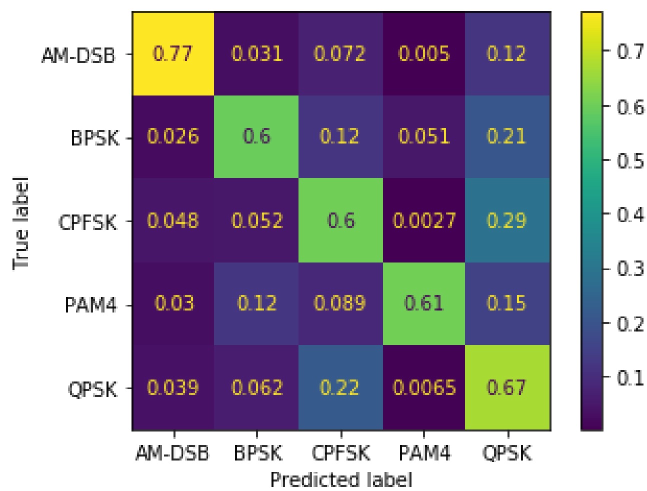

Fig.3 The resulted confusion matrix for the testing of the classifier

The precision of the classification for each modulation type is found to be high as the 4PAM precision is 0.9 and for AM-DSB is 0.84.

The simulation results that the accuracy of this classifier has reached 0.69 showing that the recognition method based on SVMs is effective. And the automatic recognition method exhibits a satisfying performance even at very low values of SNR as -20 dB.

CONCLUSION

An overview for the automatic modulation recognition of five modulated signals, utilizing a RBF-SVM classifier without any prior knowledge information of the signals nature is in the paper. Simulation of the five digital modulation types was carried out under different SNR values in the range (-20:18) dB to give a reliable tool for the AMR. The implementation of the RBF-SVM classifier was done using the python programming language. The results and evaluation of the classifier was found to be higher than expectations in its success. The evaluation resulted in 0.69 accuracy.

These results shows the possibility of correct recognition of modulated signals below 0 dB with acceptable performance.

REFERENCES

[1] E.E. Azzouz and A.K. Nandi, "Automatic Modulation Recognition of Communication Signals.", Kluwer Academic Publishers, USA, 1996.

[2] M.L. D. Wong, and A.K. Nandi, "Automatic digital modulation recognition using spectral and statistical features with multi-layer perceptrons," Sixth International Symposium on Signal Processing and its Applications (ISSPA), Kuala Lumpur, Malaysia, 2001, pp. 390-393.

[3] Jide Julius Popoola, "Automatic recognition of both inter and intra classes of digital modulated signals using artificial neural network" Journal of Engineering Science and Technology, Vol. 9, No. 2 ,2014, pp. 273 – 285.

[4] Zhilu Wu, Xuexia Wang, Zhenzhen Gao, and Guanghui Ren," Automatic Digital Modulation Recognition Based on Support Vector Machines", International Conference on Neural Networks and Brain, 2005, pp. 1025-1028.

[5] L. Wang and Y. Ren, "Recognition of digital modulation signals based on high order cumulants and support vector machines," , ISECS International Colloquium on Computing, Communication, Control, and Management, 2009, pp. 271-274.

[6] A. Wang and R. Li, "Research on Digital Signal Recognition Based on Higher Order Cumulants," International Conference on Intelligent Transportation, Big Data & Smart City (ICITBS), 2019, pp. 586-588.

[7] W. Xie, S. Hu, C. Yu, P. Zhu, X. Peng and J. Ouyang, "Deep Learning in Digital Modulation Recognition Using High Order Cumulants," in IEEE Access, vol. 7, 2019, pp. 63760-63766.