Applied Soft Computing 11 (2011) 428–435

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Classification of communications signals using an advanced technique

A. Ebrahimzadeh*, S.E. Mousavi

Faculty of Electrical and Computer Engineering, BABOL University of Technology, Iran

ARTICLE INFO

Article history:
Received 19 June 2007
Received in revised form
10 December 2008
Accepted 6 December 2009
Available online 16 December 2009

Keywords:
Pattern recognition
Signal classification
Neural network
Swarm intelligence
Cross-validation
Higher order moments
Higher order cumulants

ABSTRACT

Because of rapid growing of radio communication technology of late years, importance of automatic classification of digital signal type is rising increasingly. This paper presents an advanced technique that identifies a variety of digital signal types. This method is a hybrid heuristic formed by a radial basis function neural networks (as a classifier) and particle swarm optimization technique. A suitable combination of higher order statistics up to eighth are proposed as the prominent characteristics of the considered signals. In conjunction with neural network we have used a cross-validation technique to improve the generalization ability. Experimental results indicate that the proposed technique has high percentage of correct classification to discriminate different types of digital signal even at low SNRs.

1. Introduction

Because of rapid growing of radio communication technology of late years, importance of monitoring of radio waves is rising increasingly. Communication signals travel in space with different formats. It is being demanded to identify signal mode of radio wave by a high reliability automatically in radio wave monitoring in communication technology environment of the modern times that developed in altitude. Therefore, recognition of the digital signals is an important subject for novel communication systems. It is important for both the civilian and military domain. For the civilian authorities, this includes signal confirmation, interference confirmation, spectrum management and making sure that the guidelines for radio communication are followed. Knowledge of which signal type is used can provide valuable information and is also crucial in order to retrieve the information stored in the signal. In the military domain, signal type classification can be used for electronic warfare purposes like threat detection analysis and warning. It can further assist in the decision of appropriate counter measures like signal jamming. Signal type classification is also believed to play an important part in future 4G software radios [1]. The general idea behind the software radio architecture is to perform a considerable amount of the signal processing in software instead of it being defined in hardware. This would enable the radio to adapt to a changing environment and user requirements by simply updating the software or by using adaptable software systems. In such scenarios, a broadcaster could for example change to appropriate modulation schemes according to the capacity of the channel. A receiver incorporating automatic modulation recognition could then handle this in real time.

In the past, signal type recognition relied mostly on operators scanning the radio frequency spectrum with a wide-band receiver and checking it visually on some sort of display. Clearly, these methods relied very much on the operators' skills and abilities. These limitations then led to the development of more automated signal type recognizers. One semi-automatic approach was to run the received signal through a number of demodulators and then have an operator determine the modulation format by listening to the output of each demodulator. This approach is however not very practical anymore due to the new digital techniques that transfer both voice and data. Then automatic signal classification techniques started to emerge.

Automatic signal type classification techniques, usually, divided two principle techniques. One is the decision theoretic approach and the other is pattern recognition. Decision theoretic approaches use probabilistic and hypothesis testing arguments to formulate the recognition problem [2,3]. These methods suffer from their very high computational complexity, difficulty to implementation and lack of robustness to model mismatch. Pattern recognition approaches, however, do not need such careful treatment. They are easy to implement. PR approaches can be further divided into

* Corresponding author.
E-mail addresses: abrahamzadeh@yahoo.com (A. Ebrahimzadeh), s.e.mousavi@yahoo.com (S.E. Mousavi).

1568-4946/$ – see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.asoc.2009.12.001

two subsystems: the feature extraction subsystem and the classifier subsystem. The former extracts prominent characteristics from the raw data, which are called features, and the latter is a classifier [4–17]. Selection of both classifier and features are most serious problem in modulation classification.

In [4] the authors introduced a modulation classifier based on the zero-crossing characteristic of the intercepted signal. The considered signal types were: BPSK, QPSK, 8PSK, BFSK, 4FSK, 8FSK. The decision about the modulation type is based on the variance of the zero-crossing interval sequence, the frequency and phase difference histograms. In [5], it is proposed a technique that is based on the constellation shape. This technique used a Fuzzy-C means clustering method for classification of PSK4, PSK8 and QAM16. The accuracy rate of the identification exceeded 90% for SNR >5 dB. In [6], the authors proposed a technique for identification ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4 signals. The classifier is based on a decision flow. These digital signal types have been identified with a success rate around 90% at SNR = 10 dB. In [7], the authors proposed a technique based on elementary fourth-order cumulants. In [8], the authors proposed a classifier to discriminate among ASK, 4DPSK, 16QAM and FSK digital signals. The chosen features are: the kurtosis of the signal, the number of peaks in the phase probability density function (PDF) and the mean of the absolute value signal frequency. A fuzzy classifier was used in this technique. For SNR >5 dB, the identifier worked properly. When SNR was less than 5 dB, the performance was worse. In [9], the authors proposed using the multi-layer perceptron (MLP) neural network with back-propagation (BP) learning algorithm for automatic signal type identification. They showed that neural network classifier outperforms other classifiers such as K-Nearest Neighbor (KNN). In [10], power spectral density (PSD) measurements were used in conjunction with neural networks to identify the signal's type. This approach worked well for signals of interest whose power content distinctively varied with changes in frequency. It did not work as well with signal types like PSK. In [11], the authors introduced two classifiers: neural network classifier and fixed threshold classifier, for analog and digital modulation recognition. They showed that the neural network classifier has a higher performance than the threshold classifier. In [12], the authors used the mean and the next three moments of the instantaneous characteristics as the features of signal type classification. They used different classifiers and showed that the artificial neural network (ANN) has better performance than K-Nearest Neighbor classifier and the well-known binary decision trees. They reported a success rate of 90% with SNR ranges 15–25 dB. In [13], the authors proposed an identifier based on cyclic spectral features for identification of AM, USB, LSB, FM, ASK, FSK, BPSK, QPSK and SQPSK. It was claimed that cyclic spectrum posses more advantage than power spectrum in signal type recognition. The success rate of this identifier is reported around 90% with SNR ranges 5–25 dB. In [14], the authors used the features that proposed in [6] and a MLP neural network as the classifier. This identifier showed a success rate about 93% at SNR = 8 dB for identification of ASK2, ASK4, PSK2, PSK2, FSK2, FSK4, FSK4 and QAM16 digital signals. In [15], the authors proposed four features to classify ASK2, ASK4, PSK2, PSK4, FSK2 and FSK4. The features were extracted based on two main processing steps. The first step is the multiplication of two consecutive signal values. In the second step, the mean, the kurtosis of real and imaginary parts of the quantity obtained in the first step were used as the input features of the classifier. In [16], the authors have done a comparative study of implementation of feature extraction and classification algorithms based on discrete wavelet decompositions and Adaptive Network Based Fuzzy Interference System (ANFIS) for recognition of ASK8, FSK8, PSK8 and QASK8. In [17], the authors proposed a numerical method for identification of PSK2, PSK4, and PSK8 in fading environments.

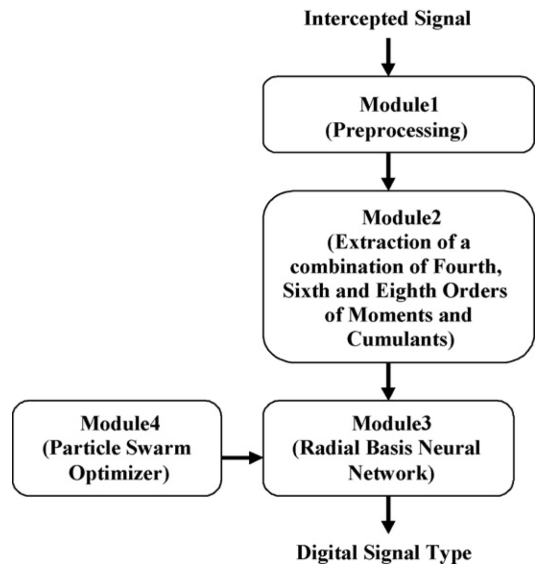

Fig. 1. General scheme of proposed technique.

Literature review shows the techniques that use artificial neural networks as the classifiers, have better performance than other techniques. In ANNs the threshold at each node is chosen automatically and adaptively and the time order of the key features does not affect the probability of correct decision of a modulation type of signal, while many other algorithms, especially those utilizing the decision-theoretic approach, have to choose the suitable threshold for each key feature and perform with different success rates at the same SNR by applying the extracted key features in a different order in the recognition algorithm [6]. Among the ANNs, the multi-layer perceptron is perhaps the most widely used neural network model, being easy to understand and easy to implement. Its main drawback is that the training procedure often gets stuck at a local optimum of the cost function; also has a slow convergence speed and might at times diverge because of the learning algorithm that is used in it (e.g. back-propagation). In this paper, we have used the radial basis network (RBFN). This model avoids the difficulty of local optimum by conducting the training procedure in two steps. We have proposed an optimizer, i.e. particle swarm optimization (PSO) to build a RBFN that solves signal type classification problem. Also cross-validation method is used to improve the generalization ability. As said features have vital role in signal classification. Indeed one of the main reasons that most techniques have limitations on recognition of digital signal types is the features that they utilize. In this paper, we have proposed a selected combination of higher order moments and higher order cumulants up to eighth as the effective features of the considered signals.

Fig. 1 shows the general scheme of proposed technique. Module1 is the preprocessing module that performs actions such as: rejection of noise outside of signal bandwidth, carrier frequency estimation (or to be known), recovery of complex envelope, etc. This stage is similar in most of methods and we would not explain it more. Module 2 is feature extraction and selection module. This module extracts and selects the suitable characteristics for signal representation and will be explained in Section 2. Section 3, describes the RBFN. Section 4 presents particle swarm intelligence. Section 5, describes implementation of PSO-RBFN. In Section 6 some simulation results are shown. Finally, Section 7 concludes the paper.