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Intelligent digital signal-type identification

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Abstract

Digital signal-type identification is an important issue in communication intelligence system. Most of the proposed identifiers (techniques) can only identify a few kinds of digital signal and/or low order of digital signals. They usually require high levels of signal-to-noise ratio (SNR). This paper presents an intelligent technique that includes a variety of digital signals. In this technique, a combination of the higher-order moments and the higher-order cumulants up to eighth are proposed as the effective features for representation of the considered digital signals. A multilayer perceptron neural network with resilient back propagation learning algorithm is utilized to determine class of the received signal. The numbers of nodes in the hidden layer, along with the selection of input features are optimized using a genetic algorithm. Simulation results show that the proposed technique has high performance for identification the different digital signal types even at very low SNRs. This high performance is achieved with only seven selected features and the least possible number of nodes in the hidden layer, which have been optimized using the genetic algorithm.

Keywords: Statistical pattern recognition; Signal-type identification; Neural network; Learning algorithms; Optimization; Higher-order moments; Higher-order cumulants

1. Introduction

Automatic signal-type identification plays an important role for various applications and purposes. For example, in military domain, it can be employed for electronic surveillance, interference identification, monitoring; in civil applications, it can be used for spectrum management, network traffic administration, different data rate allocation, signal confirmation, interference identification, software radios, multidrop networks, intelligent modems, etc. Owing to the increasing usage of digital signals in the novel technologies, in this paper we have focused on the identification of these signal types.

Generally, automatic signal-type identification methods fall into two main categories, decision theoretic (DT) and pattern recognition (PR). DT approaches use probabilistic and hypothesis testing arguments to formulate the identification problem (Martret and Boitea, 1998; Wei and Mendel, 2000; Panagotiou and Polydoros, 2000). The major drawbacks of DT approaches are their too high computational complexity, lack of robustness to the model mismatch, the difficulties of forming the right hypothesis as well as careful analysis that are required to set the correct threshold values. Also, DT approaches have limitation in order to consider the different types of digital signal. PR approaches, however, do not need such careful treatment. They are easy to implement. PR approaches can be further divided in two main subsystems: the feature extraction subsystem and the classifier subsystem. The former extracts prominent characteristics from the received signal, which are called features and the latter determines the class of the incoming signal (Azzouz and Nandi, 1995; Chani and Lamontagne, 1993; Clair et al., 1997; Ebrahimzadeh and Seyedin, 2005; Hsue and Soliman, 1990; Lopatka and Macrej, 2000; Mingquan et al., 1996; Mobasseri, 2000; Nandi and Azzouz, 1998; Swami and Sadler, 2000; Sehier, 1993; Zhao et al., 2003).

In Hsue and Soliman (1990), the authors introduced an identifier based on the zero-crossing characteristic of the intercepted signal. The considered signal types were BPSK, QPSK, 8PSK, BFSK, 4FSK and 8FSK. The decision

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about the modulation type is based on the variance of the zero-crossing interval sequence, the frequency and phase difference histograms. Mobasseri (2000), proposed an identifier that is based on the constellation shape. He 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 Azzouz and Nandi (1995), 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 Swami and Sadler (2000), the authors proposed a digital signal-type identification technique based on elementary fourth-order cumulants. In Lopatka and Macrej (2000), the authors proposed a technique to discriminate among amplitude shift keying (ASK), 4DPSK, 16QAM and frequency shift keying (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. Chani and Lamontagne (1993) proposed a technique 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). Clair et al. (1997), power spectral density 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 phase shift keying (PSK). Nandi and Azzouz (1998), 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 Sehier (1993), the authors used the mean and the next three moments of the instantaneous characteristics as the features of signal-type identification. They used different classifiers and showed that the artificial neural network has better performance than KNN classifier and the well-known binary decision trees. They reported a success rate of 90% with SNR ranges 15–25 dB. In Mingquan et al. (1996), 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 Ebrahimzadeh and Seyedin (2005), the authors used a combination of the symmetry, fourth-order cumulants and fourth-order moments of the received signals as the features for identification of PSK2, PSK4, QAM8, ASK2 and ASK4. The classifier was a modified MLP neural network (with few output nodes). They reported a success rate about 92% at SNR of 8 dB. In Zhao et al. (2003), the authors used the features that proposed in Azzouz and Nandi (1995) 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.

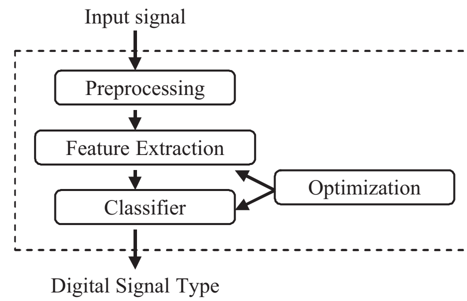

Fig. 1. General scheme of the proposed identifier.

From the published works, it can be found that (a) most of the proposed identifiers can only recognize low orders of digital signals and/or a few kinds of digital signals, (b) usually, the proposed techniques require high SNRs and (c) the identifiers, which use MLP neural networks as the classifier, have higher performances. In this paper, firstly, we present a highly efficient identifier. In this identifier, we propose a combination of the higher-order moments and higher-order cumulants up to eighth as the effective features (for representation of digital signals). A MLP neural network with resilient backpropagation learning algorithm is utilized as the classifier. This identifier has high performances for discrimination of the considered digital signal types. However the number of features that we have used was a lot. Therefore, we have decided to use a genetic algorithm (GA) for feature selection as well as in order to optimize the structure of the classifier. Fig. 1 shows the general scheme of this intelligent identifier. In this figure, the preprocessing module performs: the rejection of noise outside of the signal bandwidth, carrier frequency estimation (or to be known), recovery of the complex envelope, etc. This module is similar to signal-type identification techniques and hence will not be explained here. Section 2 introduces the considered digital signals. Section 3 describes the feature extraction module. Section 4 presents the classifier that is utilized in this paper. Section 5 introduces the GA for optimization. Section 6 shows some simulation results. Finally, Section 7 concludes the paper.

2. Considered digital signals set

In digital communications, based on changes in the frequency of message, amplitude of message, phase of message or changes in amplitude and phase, there are four main digital signal formats: FSK, ASK, PSK and