An Intelligent System for Classification of the Communication Formats Using PSO

Ata E. Zadeh Shermeh and Reza Ghaderi
Faculty of Electrical and Computer Engineering,
Babol Noushirvani University of Technology, Iran
E-mail: ataebrahim@yahoo.com, r.ghaderi@nit.ac.ir

Text Automatic identification of digital signal types is of interest for both civil and military applications. This paper presents an efficient signal type identifier that includes a variety of digital signals. In this method, a combination of higher order moments (HOM) and higher order cumulants (HOC) are used as the features. A multi-layer perceptron neural network with SASS learning algorithm is proposed to determine the membership of the received signal. We have used swarm intelligence (SI) for feature selection in order to reduce the complexity of the classifier. Simulations results show that the proposed method has high performance for identification of different kinds of digital signal even at very low SNRs. This high efficiency is achieved with only seven features, which have been selected using particle swarm optimizer.

Povzetek: Opisana je metoda za identifikacijo digitalnih signalov.

1   Introduction

Automatic signals type recognition is an important topic for both the civil and military domain. Signal type recognition 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 times.

Automatic signal classification methods, 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 [7]. Pattern recognition approaches, however, do not need such careful treatment. They are easy to implement. They can be further divided into 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 [4-14].

In [9], for the first time, Ghani and Lamontagne 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. The approach was to transform the signal into its power spectrum and then to use that power spectrum as input to a backpropagation neural network. 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. The overall success rate is over 96% at the SNR of 15 dB. In [12], the authors proposed an identifier for the identification of PSK2, PSK4, PSK8, OQPSK, MSK, QAM16, QAM32, FSK2 and FSK4 signal types. The features chosen to characterize the signal types are the mean and the next three moments of the instantaneous characteristics. They used different classifiers and showed that the artificial neural network has better performance than K-Nearest Neighbor (KNN) classifier and the well known binary decision trees. They reported a success rate of 90% with SNR ranges 15-25 dB. However, the performance for lower SNRs is reported to be less than 80%. 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. A full-connected backpropagation neural network is used for classification in that research. The success rate of this identifier is reported around 90% with SNR ranges 5-25 dB. In [14], the authors have used a combination of the symmetry, fourth order cumulants and power moments of the received signals as the features for identification of PSK2, PSK4, PSK8, QAM16 and QAM32. The classifier was a modified MLP neural network (with few output nodes). They reported a success rate about 92% at SNR of 8dB. In [15], the authors have introduced an identifier based on discrete wavelet decompositions and adaptive network based fuzzy interference system for recognition of ASK8, FSK8, PSK8 and QASK8.

Most of the methods can only recognize a few types of digital signal and/or lower order of digital signal types. They usually need high SNRs in order to achieve the minimum acceptable performance (80%). Basically, this is due to the classifier and the features that are used. Finding the suitable features is a very important step for recognition of these digital signals. From the published works it can be found that the methods, which use the higher order statistical features, are able to include the digital signal types such as QAM and higher orders of digital signals [6-12]. In this paper we have used a combination of the higher order moments and higher order cumulants (up to eighth) as the effective features for recognition of the considered digital signals. The identifiers that use artificial neural networks (ANNs) as the classifier have high performances [12-14]. In this paper we have used a multi-layer perceptron (MLP) neural network with self adaptive step-size (SASS) learning algorithm as the classifier [15]. We have used particle swarm optimization, in order to reduce the complexity of the proposed identifier.

The paper is organizes as follows. Section 2 describes the feature extraction module. Section 3 presents the classifier. Optimization module is introduced in Section 4. Section 5 shows some simulation results. Finally, Section 6 concludes the paper.

2   Feature extraction

A typical pattern recognition system after doing some pre-processing operations, often reduce the size of a raw data set by extracting some distinct attributes called features. The need for feature extraction comes to scene due to the possible inability to use the raw data. These features define a particular pattern. In the signal recognition area, choosing the good features, not only enable the classifier to distinguish more and higher digital signals, but also help to reduce the complexity of the classifier.

In this paper we have considered the following digital signals: ASK2, ASK4, ASK8, PSK2, PSK4, PSK8, QAM16, QAM32, QAM64, Star-QAM8, and V32. For simplifying the indication, the signals ASK2, ASK4, ASK8, PSK2, PSK4, PSK8, QAM16, QAM32, QAM64, Star-QAM8, and V32 are substituted with P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8, P_9, P_{10}, and P_{11} respectively. Different

types of the digital signal have different properties; therefore finding the proper features in order to identify them (especially in case of higher order and/or non-square) is a difficult task. Based on our researches, a combination of the higher order moments and higher order cumulants up to eighth make provide a fine way for discrimination of the considered digital signal types.

Probability distribution moments are a generalization of concept of the expected value, and can be used to define the characteristics of a probability density function [16]. The auto-moment of the random variable may be defined as follows:

$$M_{pq} = E[s^{p-q}(s^*)^q] \qquad (1)$$

where p called moment order and s^* stands for complex conjugation. Now, consider a zero-mean discrete based-band signal sequence of the form $s_k = a_k + jb_k$. Using the definition of the auto-moment, the expressions for different order may be easily derived.

Consider a scalar zero mean random variable s. The symbolism for p^{th} order of cumulant is:

$$C_{pq} = Cum[\underbrace{s,...,s}_{(p-q)terms}, \underbrace{s^*,...,s^*}_{(q)terms}] \qquad (2)$$

3   Classifier

We have used a MLP neural network as the classifier. A MLP neural network consists of an input layer of source nodes, one or more hidden layers of computation nodes (neurons) and an output layer [17]. The number of nodes in the input and the output layers depend on the number of input and output variables, respectively. In this paper a single hidden layer MLP neural network was chosen as the classifier. The issue of learning algorithm is very important for MLP. Backpropagation (BP) learning algorithm is still one of the most popular algorithms. In BP a simple gradient descent algorithm updates the weight values. However under certain conditions, the BP network classifier can produce non-robust results and easily converge to local minimum. Moreover it is time consuming in training phase. New algorithms have been proposed so far in order to network training. However, some algorithms require much computing power to achieve good training, especially when dealing with a large training set.

In this paper, SASS learning algorithm is used [17]. SASS is an adaptive step-size method. it is based on the bisection method for minimization in one dimension, in which the minimum of a valley is found by taking a step in the descent direction of half the previous step. The method has been adapted to allow the step-size to both increase and decrease. It uses the same update rule resilient but updates Δ_{ij} differently. It uses two previous signs and has an increment factor of 2.

$$\Delta_{ij(t)} = \begin{cases} 2.0 * \Delta_{ij}(t-1); if \quad \dfrac{\delta E}{\delta w_{ij}}(t-1)\dfrac{\delta E}{\delta w_{ij}}(t) \geq 0 \\[2mm] \qquad and \quad \dfrac{\delta E}{\delta w_{ij}}(t-2)\dfrac{\delta E}{\delta w_{ij}}(t) \geq 0 \quad (3) \\[4mm] 0.5 * \Delta_{ij}(t-1); \quad otherwise \end{cases}$$

This update value adaptation process is then followed by the actual weight update process, which is governed by the following equation:

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \qquad (4)$$

4 Swarm intelligence

There were a large number of features involved in the study as it was found in Section 2. Although some of these features may carry good classification information when treated separately, there is little gain if they are combined together (due to sharing the same information content). The easiest way to reduce the number of features is feature selection. The advantage of feature selection is that one can use the least possible number of features without compromising the performance of the identifier. In this paper we use the particle swarm optimization (PSO) for feature subset selection.

The particle swarm optimization (PSO) algorithm was first introduced in 1995 [18]. The basic operational principle of the particle swarm is reminiscent of the behavior of a group of a flock of birds or school of fishes or the social behavior of a group of people. Each individual is considered as a volume-less particle (a point) in the N-dimensional search space. The index of the best particle among all the particles in the population (global model) is represented by the symbol g. The index of the best particle among all the particles in a defined topological neighborhood (local model) is represented by the index subscript l. The particle variables are manipulated according to the following equation (global model [18]):

$$v_{in}(t) = w_i * v_{in}(t-1) +$$

$$c_1 * rand1() * (p_{in} - x_{in}(t-1)) + \qquad (9)$$

$$c_2 * rand2() * (p_{gn} - x_{in}(t-1))$$

$$x_{in}(t) = x_{in}(t-1) + v_{in}(t) \qquad (10)$$

where n is the dimension $(1 \leq n \leq N)$, c_1 and c_2 are positives constants, $rand1()$ and $rand2()$ are two random functions in the range [0,1], and w is the inertia weight. $X_i(t) = (x_{i1}(t), x_{i2}(t),...,x_{iN}(t))$ presents the the ith particle at time step t. $P_i(t) = (p_{i1}, p_{i2},..., p_{iN})$ records the best previous position (the position giving the best fitness value) of the ith particle. $V_i(t) = (v_{i1}(t), v_{i2}(t),...v_{iN}(t))$ presents the rate of the position (velocity) for particle i at the time step t.

The constants c_1 and c_2 in above equation represent the weighting of the stochastic acceleration terms that pull each particle toward *pbest* and *gbest* positions. Thus,

adjustment of these constants changes the amount of 'tension' in the system. Low values allow particles to roam far from target regions before tugged back, while high values result in abrupt movement toward, or past, target regions. The inertia weight w controls the impact of the previous histories of velocities on the current velocity, thus influencing the trade-off between global (wide-ranging) and local (nearby) exploration abilities of the 'flying points'. By linearly decreasing the inertia weight from a relatively large value to a small value through the course of the PSO run (total number of generations prior termination), the PSO tends to have more global search ability at the beginning of the run while having more local search ability near the end of the run [19].

5 Simulation results

This section presents the some simulation results of the proposed identifier. All signals are digitally simulated in MATLAB editor. We assumed that carrier frequencies were estimated correctly (or to be known). Thus, we only considered complex base-band signals. Gaussian noise was added according to SNRs, –5, 0, 5, 10, and 15dB to the simulated signals. Each signal type has 2400 realizations. These are then divided into training, validation and testing data sets. The activation functions of tan-sigmoid and logistic were used in the hidden and the output layers, respectively. The MSE is taken to be10^{-6}. The MLP classifier is allowed to run up to 5000 training epochs. Based on our extensive experiments it seems that the number of 20 neurons is adequate for reasonable identification.

5.1 Performance of identifier without feature selection

In this subsection, we evaluate the performance of straight proposed identifier (SPROI), i.e. full features are used. Tables 1-2 show the correct matrix of identifier at two selected values of SNR. Table 3 shows the performances of the identifier at various SNRs. It can be seen that the performances of identifier is generally very good at low SNRs. Also, we have evaluated the performance of the identifier at a high SNR value. Table 4 indicates the training performance of identifier at SNR= 50dB. The classifier can show up to 100% success rate.

Table3: Correct matrix of the identifier (without feature selection) at SNR=5dB.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}
P_1	97.2										
P_2		97.8									
P_3			96.6								
P_4				100							
P_5					96						
P_6						97					
P_7							93.4				
P_8								97			
P_9									94.5		
P_{10}										98	
P_{11}											94.5

Table2: Correct matrix of the identifier (without feature selection) at SNR=10dB.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}
P_1	99										
P_2		100									
P_3			98.8								
P_4				100							
P_5					98						
P_6						100					
P_7							98.6				
P_8								98			
P_9									98.4		
P_{10}										98.2	
P_{11}											98.4

Table3: The performances of the identifier (without feature selection) at different SNR values.

SNR	Training	Testing
-5	85.45	83.76
0	89.85	88.52
5	96.75	96.55
10	98.90	98.85
15	99.25	99.14

Table4: The performances of identifier (without feature selection) at SNR=50dB.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}
P_1	100										
P_2		100									
P_3			100								
P_4				99.6							
P_5					100						
P_6						100					
P_7							100				
P_8								99.6			
P_9									100		
P_{10}										99.8	
P_{11}											99.4

As mentioned the speed of learning algorithm is an important issue for MLP. The efficiency of the learning algorithm affects the amount of experimentation that can be done. To indicate the effectiveness of chosen learning algorithm (SASS), we have compared it with the SUPERSAB learning algorithm that is an adaptive learning rate algorithm [20]. In SUPERSAB learning algorithm each weight w_{ij} , connecting node j with node i, has its own learning rate that can vary in response to error surface. The system that uses MLP with SUPERSAB learning algorithm as the classifier is named as TECH2. Based our experiments, any number in the vicinity of 40 neurons seems to be adequate for reasonable classification. Other simulations setup is the

same. Table 5 shows the performance of TECH2. Table 8 presents the comparison between SPROI (that uses MLP with SASS learning algorithm as the classifier) and TECH2. It can be seen that the performance of the SPROI (that uses MLP with SUPERSAB learning algorithm as the classifier). It can bee seen that SPRRO has better performance than TECH2.

Table7: The performance of TECH2 at different levels of SNR.

SNR	Training	Testing
-5	73.46	72.35
0	82.42	80.24
5	86.70	85.42
10	94.64	92.45
15	96.25	94.65

Table6: Comparison between SPROI and TECH2: the testing performance and the number of epochs that are needed.

	SASS		SUPERSAB	
SNR	Passed Epochs	Testing	Passed Epochs	Testing
-5	725	83.76	1245	72.35
0	324	88.52	685	80.24
5	565	96.55	1575	85.42
10	364	98.85	978	92.45
15	485	99.14	1245	94.65

5.2   Performance of the identifier with using the optimizer

We have tested the identifier using several features selected using PSO. The selection of the PSO parameters plays an important role in the optimization.

Table 7 shows the performances of the identifier using four features selected by PSO. Table 8 shows this performance using seven features selected by PSO. Table 9 show the performance of the identifier using eighteen features selected by PSO. Also in these tables the performances of identifier without feature selection is showed. It can be seen that in Table 8 the identifier records a performance degradation less than 1% only at SNR= -5dB. For other levels of SNR, the difference is negligible. Thus it can be said that the proposed method achieves high performance on most SNR values with only seven features that have been selected using PSO. Tables 10-11 show the correct matrices of identifier at SNR= 5 dB and SNR=10 with seven features that have been selected by PSO. It is found that proposed is able to identify the different types of digital signal with high accuracy only seven selected features using PSO.

Table7: Testing performance (TP) of the identifier with five features selected using PSO.

SNR	TP with applying PSO	TP without PSO
-5	80.15	83.76
0	83.25	88.85
5	91.20	96.55
10	94.68	98.85
15	97.51	99.14

Table8: Testing performance (TP) of the identifier with seven features selected using PSO.

SNR	TP with applying PSO	TP without PSO
-5	82.90	83.76
0	88.25	88.85
5	96.18	96.55
10	98.50	98.85
15	99.02	99.14

Table9: Testing performance (TP) of the identifier with twenty features selected using PSO.

SNR	TP with applying PSO	TP without PSO
-5	83.45	83.76
0	88.60	88.85
5	96.25	96.55
10	98.65	98.85
15	99.08	99.14

Table12: Correct matrix of PROI with only seven features selected using PSO at SNR=5dB.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}
P_1	97										
P_2		97									
P_3			96.5								
P_4				100							
P_5					95						
P_6						97					
P_7							92.5				
P_8								97			
P_9									94		
P_{10}										97.5	
P_{11}											94.5

Table13: Correct matrix of PROI with only seven features selected using PSO at SNR=10dB.

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}	P_{11}
P_1	99										
P_2		100									
P_3			99								
P_4				100							
P_5					97						
P_6						100					
P_7							98				
P_8								98			
P_9									97.5		
P_{10}										97	
P_{11}											98

As mentioned the features play a vital role in signal identification. In order to indicate the effectiveness of the chosen features, we have used the features that have been introduced in [7]. We name this identifier as THECH3. Other simulations setup is the same. Figure1 show a comparison between TECH3 and our proposed identifier (PROI) at different SNRs. Results imply that our chosen features have effective properties in signal representation.
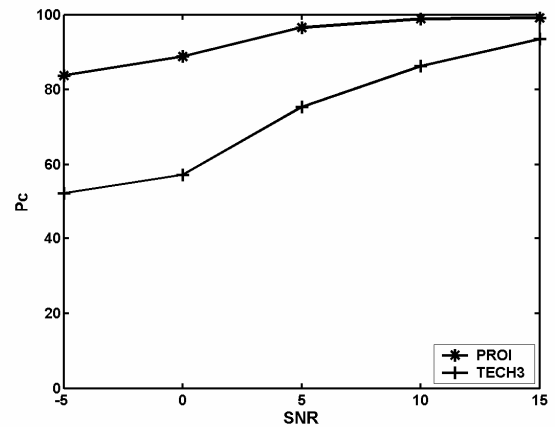
Figure1: Performances comparison between PROI and TECH3.

6   Conclusions

Automatic signal type identification is an important issue for both the civilian and military domain. Most of the techniques can only identify a few kinds of digital signal and/or lower orders of digital signals. They usually need high SNRs for identification of the considered digital signals. These problems are mainly due to two facts: the factures and the classifier that are used in the identifiers. In this paper we have proposed a number of the features, i.e. a combination of the higher order moments and the higher order cumulants (up to eighth), which have high ability in representing of the digital signal types. As the classifier, we have proposed a MLP neural network with SASS learning algorithm as the classifier. This classifier has high classification ability. By using the mentioned features and classifier, we have presented a highly efficient identifier. This identifier discriminates a lot of digital signal types with high accuracy even at very low SNRs. But there are a lot of features are used for this identification. In order to reduction the complexity of the proposed identifier we have used an optimizer, i.e. PSO. Using this idea reduces the number of features without trading off the generalization ability and accuracy. The optimized identifier also has high performance for identification of the considered different kinds of digital signal even all SNRs. This high efficiency is achieved with only seven features, which have been selected using particle swarm optimizer. One the advantage of the swarmed features selection is its simple implementation. Furthermore in PSO to switch from one approach to another approach is also easy. For future works, we can use the PSO in order to construct of the classifier as well as the features selection. Also we can consider another set of digital signal types and evaluate this technique for identification of them. We can select the proper features that introduced by others and combine them with the features that are proposed in this paper in order to have suitable

features set for identification the different types of digital signal.

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