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Type of modulation identification using Wavelet Transform and Neural Network

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Abstract. Automatic recognition of the signal modulation type turned out to be useful in many areas, including electronic warfare or surveillance. The wavelet transform is an effective way to extract signal features for identification purposes. In this paper there are M-ary ASK, M-ary PSK, M-ary FSK, M-ary QAM, OOK and MSK signals analysed. The mean value, variance and central moments up to five of continuous wavelet transform (CWT) are used as signal features. The principal component analysis (PCA) is applied to reduce a number of features. A multi-layer neural network trained with backpropagation learning algorithm is considered as a classifier. There are two research variants: interclass and intraclass recognition with a wide range of signal-to-noise ratio (SNR).

Key words: modulation identification, artificial neural networks (ANN), continuous wavelet transform (CWT).

1. Introduction

Automatic signal identification has a great influence on electronic surveillance and electronic warfare systems effectiveness. A proper signal classification makes signal demodulation or emitter identification possible. In [1] and [2] authors present methods of the automatic modulation classification (AMC) for an electronic intelligence (ELINT) purposes. One of the possible application of a radar signal waveform is modified nonlinear frequency modulation (NLFM) presented in [3] or waveforms used for synthetic aperture radar (SAR) techniques discussed in [4, 5]. Then in [6, 7] AMC methods for wireless communication systems are proposed. As a classifier there is usually an artificial neural network considered [8] or decision trees. There are also a couple of articles concerning modulation recognition algorithms using the Wavelet Transform as a method of feature extraction [9–17]. We can divide them into categories e.g. interclass and intraclass classification algorithms. The first one concerns ability to distinguish between type of modulation e.g. OOK, MSK, M-ASK, M-PSK, M-FSK or M-QAM. The second one concentrates on ability to recognize modulation order within a single class, such as BPSK, 4PSK or 8PSK. On the other hand, there are other categories of division considering e.g. a type of classifier. In that way there are two types of classification: decision-theoretic approach and pattern recognition. The first solution is based on a priori knowledge of probability functions and certain hypotheses. The second one considers features extraction. In this paper second approach is taken into consideration. The second section treats about useful properties of continuous wavelet transform (CWT) and its ability to describe base characteristics of analysed signals. In the third section authors present the identification algorithm and in the fourth one, there are given research results.

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2. CWT of modulated signal

The continuous wavelet transform (CWT) enables extraction of transient information associated with amplitude/frequency changes and phase shifts which are characteristics of modulated signals. CWT of a signal *x(t)* is defined as [18]:

$$CWT(\tau, a) = \int x(t)\psi_a^*(t)dt = \frac{1}{\sqrt{|a|}} \int x(t)\psi^*\left(\frac{t-\tau}{a}\right)dt, \tag{1}$$

where the $\psi(t)$ is called the mother wavelet and a is the scaling constant. ψ_a^* is called the baby wavelet and is the translated and scaled version of $\psi(t)$.

The complex form of a considered signal is [12]:

$$x(t) = s(t) + n(t) = \widetilde{s}(t)\exp[j(w_o t + \theta_o)] + n(t), \tag{2}$$

where $s(t)$ is the modulated complex waveform, $n(t)$ is the Gaussian white noise, w_o is the carrier frequency and θ_o is the carrier initial phase. In case of digital implementation of CWT, the integral in Eq. (1) can be replaced by summation [12]. Assuming that $t = kT = k$, $z = nT = n$ and the scale is restricted to an even integer, we could write that [12]:

$$CWT(n, a) = \frac{1}{\sqrt{a}} \sum x(k)\psi^*\left(\frac{k-n}{a}\right), \tag{3}$$

where the sampling rate T is set to unity.

The analysis presented in [9] show that for feature extraction signal normalization is needed. The identification methods of a signal were normalization used and presented in [9] and [15]. It allows to distinguish an amplitude from frequency modulation. The $|CWT(n, a)|$ with and without a median filter applied for chosen modulation types are presented in Fig. 1–5. The $|CWT(n, a)|$ of M-ASK and M-QAM signal is a multi-step function. Each level of $|CWT(n, a)|$ conforms to a specific symbol. The $|CWT(n,a)|$ of normalized M-ASK and M-QAM is a constant with peaks observed in the moment of the symbol change. The $|CWT(n,a)|$ of OOK is a two-step function and signal normalization gives the same result as normalization of M-ASK or M-QAM. Due to different values of amplitude levels and different phase transients it is possible to distinguish each of amplitude modulation types.

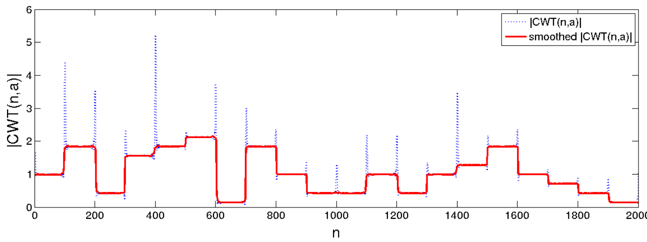

Fig. 1. $|CWT(n,a)|$ of 16-ASK with and without median filter applied

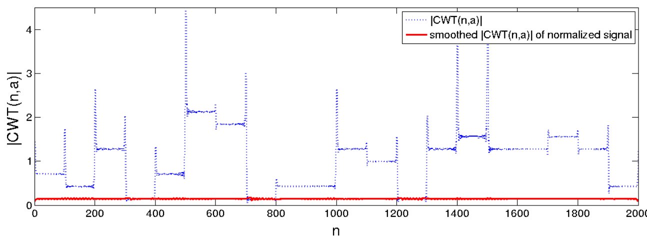

Fig. 2. $|CWT(n,a)|$ of 16-ASK and smoothed $|CWT(n,a)|$ of normalized 16-ASK

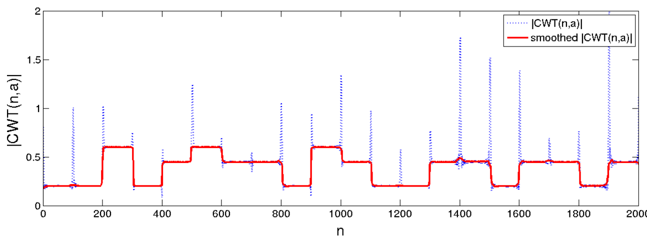

Fig. 3. $|CWT(n,a)|$ of 16-QAM with and without median filter applied

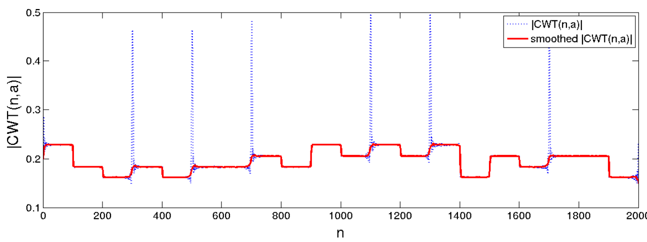

Fig. 4. $|CWT(n,a)|$ of 4-FSK with and without median filter applied

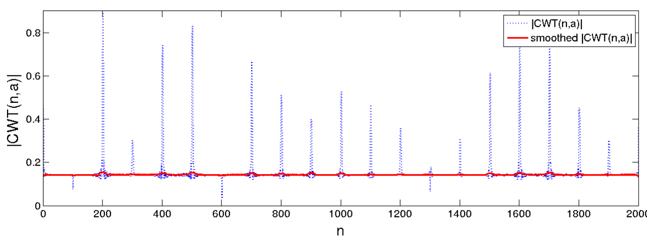

Fig. 5. $|CWT(n,a)|$ of 16-PSK with and without median filter applied

The $|CWT(n,a)|$ of M-FSK signal, the same as for M-ASK and M-QAM, is a multi-step function. The difference is noticeable after signal normalization. The $|CWT(n,a)|$ of normalized M-FSK is still a multi-step function with transients observed in the moment of the symbol change. MSK signal is considered as a special case of M-FSK with $M = 2$, continuous phase and modulation index 0.5 so there are no transients. The $|CWT(n,a)|$ of normalized MSK signal is a two step function with and without signal normalization.

The $|CWT(n,a)|$ of M-PSK signal is a constant function with and without normalization with visible peaks resulting from phase changes.

Introduced observations show that:

- The $|CWT(n,a)|$ of M-ASK, M-QAM, M-FSK is multi-step function;
- The $|CWT(n,a)|$ of MSK and OOK has two levels;
- The $|CWT(n,a)|$ of M-PSK is constant (with peaks resulting from phase changes);
- Signal normalization does not affect the $|CWT(n,a)|$ of M-PSK, M-FSK and MSK;
- Signal normalization affects $|CWT(n,a)|$ of M-ASK, M-QAM, OOK and make it constant (with peaks resulting from phase changes).

In the analysed algorithm the statistical properties of $|CWT(n,a)|$ for each modulated signal with and without normalization, and with and without a median filter applied, are used as a feature vector. In [9] the usage of central moments up to five is presented but in this research two scenarios are taken into consideration. The feature extraction algorithm consider only a mean variance and central moments up to five to show the impact of central moments order on recognition results.

3. Interclass and intraclass identification results

The researches were divided into two subsystems, the first one for interclass recognition (only classification of a modulation type) and the second one for intraclass recognition (type of modulation was known, only classification of modulation order). In both cases the features extraction was based on statistical properties of $|CWT(n,a)|$. For identification purposes the neural network – MLP (Multilayer perceptron) with a backpropagation training method was proposed, where the number of network entries were dependent on the number of PCA features. The considered scenario assumed a presence of additive Gaussian noise. The boundary value of SNR (signal-to-noise ratio) was determined for each neural network learning process e.g. in the case boundary value of SNR was set to 6dB it meant the range of SNR for simulated signals was from 6 to 20 dB. SNR value for each signal realization was randomly chosen within a given range. For interclass recognition purposes there was $|CWT(n,a)|$ of M-ASK, M-QAM, M-PSK, M-FSK, OOK and MSK calculated with and without normalization and smoothing. Analysed signals consisted of 100 symbols. Tables 1–4. show results for interclass identification with 0 dB, 4 dB, 10 dB and 20 dB value of SNR.

There were used 300 realizations of each modulation type for a neural network learning process.

Table 1
Percentage of correct interclass identification for SNR = 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	94.1%	98.2%	100%	–
moments up to 5	95%	100%	100%	100%

Table 2
Percentage of correct interclass identification for SNR range from 10 to 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	95.2%	95.7%	95.1%	–
moments up to 5	95.4%	99.9%	99.9%	100%

Table 3
Percentage of correct interclass identification for SNR range from 4 to 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	95.3%	95.2%	95.4%	–
moments up to 5	95.2%	99.3%	99.7%	100%

Table 4
Percentage of correct interclass identification for SNR range from 0 to 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	94.2%	95.2%	94.5%	–
moments up to 5	93.1%	98.1%	98.7%	98.6%

Table 5
Percentage of correct M-ASK identification for SNR range from 4 to 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	100%	100%	100%	–
moments up to 5	100%	100%	100%	100%

Table 6
Percentage of correct M-FSK identification for SNR range from 4 to 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	95.6%	96.9%	96.1%	–
moments up to 5	91.8%	92.5%	88.2%	90%

Table 7
Percentage of correct M-QAM identification for SNR range from 4 to 20 dB

	Number of features (PCA)			
	3	5	7	10
mean and variance	100%	100%	100%	–
moments up to 5	100%	100%	100%	100%

For an intraclass scenario there were following modulations analysed: 4-ASK, 8-ASK, 16-ASK, 2-PSK, 4-PSK, 8-PSK, 16-PSK, 4-FSK, 8-FSK, 16-FSK, 8-QAM, 16-QAM. There were used 300 realizations of each modulation type for a neural network learning process.

The performance of the neural network applied as a classifier was tested for 1000 randomly chosen modulation types and orders. Parameters of simulated signals, e.g. frequency deviation was randomly changed in a certain range.

In case of M-PSK intraclass classification information about a modulation order is related with peaks values. For high noise level (SNR < 22 dB) peaks from phase changes cannot be distinguished from noise, that was described in [10] and was not wider considered in our experiment. Hence, only classification within BPSK and M-ary PSK was possible so there are no table with results for PSK order recognition. Figure 7 shows features distribution for SNR $\in [10, 20]$ dB and with only first three PCA features.

In case of M-ASK or M-QAM intraclass classification has high correctness and ability to separate each modulation order with first three PCA features is presented in Fig. 6.

For calculation purposes software from [19] was used.

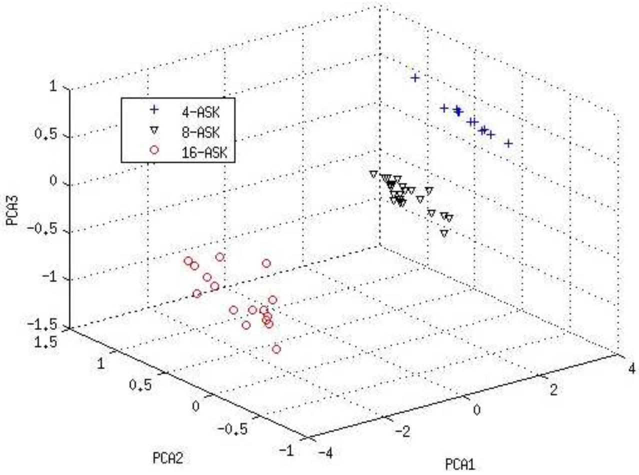

Fig. 6. Feature distribution for M-ASK intraclass recognition (SNR $\in [10, 20]$ dB)

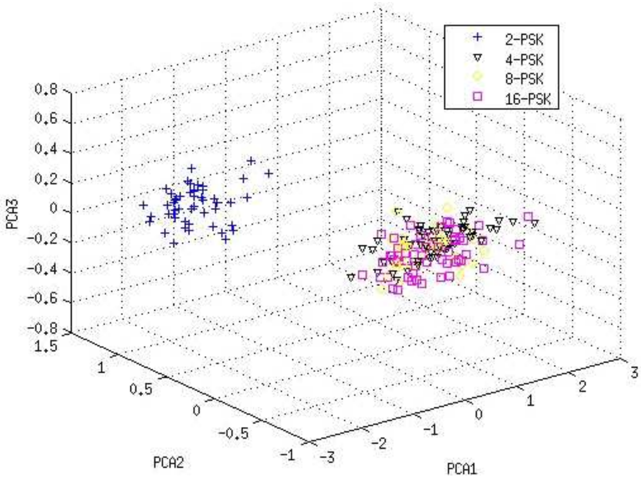

Fig. 7. Feature distribution for M-PSK intraclass recognition (SNR $\in [10, 20]$ dB)

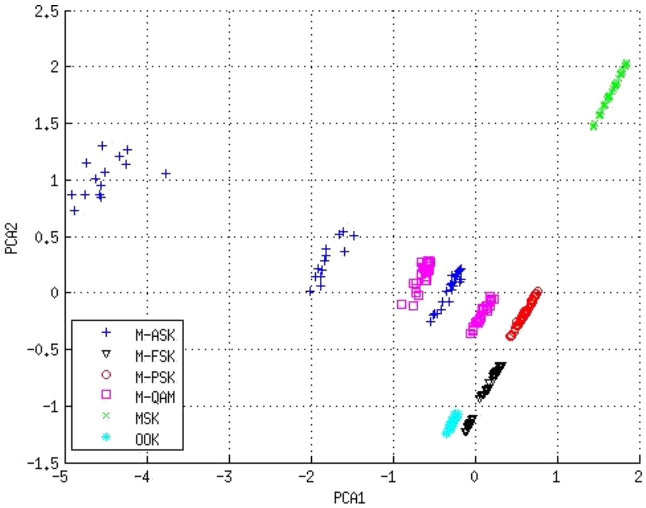

Fig. 8. Feature distribution for interclass recognition (SNR $\in [10, 20]$ dB)

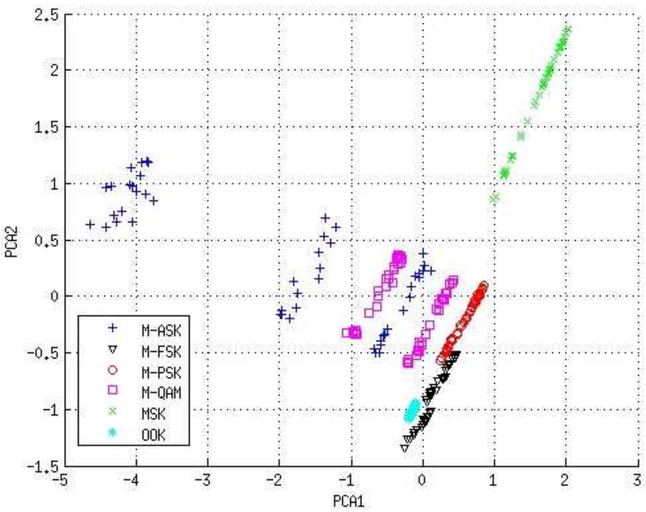

Fig. 9. Feature distribution for interclass recognition (SNR $\in [4, 20]$ dB)

4. Conclusions

In this paper, the recognition algorithm using CWT and neural network as classifier, was analysed. One of the most important features of identification algorithm is its robustness to low SNR level. Researches show that the considered method gives possibility to achieve high accurateness of identification with a low SNR level. It is presented in [9] that using a radial network as classifier could give a higher percentage of the correct recognition.

However, there are some problems to resolve, e.g. in case of PSK intraclass classification using additional algorithm is necessary to distinguish M-PSK order. A similar problem could be observed in case of M-FSK classification, where effectiveness of recognition is lower than for M-ASK or M-QAM. These problems are considered in [11]. On the other hand,the analysis shows that in some cases an increasing number of statistic parameters of $|CWT(n, a)|$ do not ensure a higher percentage of the correct classification. For M-ASK and M-QAM intraclass recognition using mean and variance as features is enough. In case of using PCA algorithm it is very important to choose a proper number of features. The number of features shall be low enough to improve a neural network learning speed, and high enough to assure expected effectiveness of recognition.

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