Automatic Modulation Recognition of Digital Signals using Wavelet Features and SVM

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Abstract — **This paper presents modulation classification method capable of classifying incident digital signals without a priori information using WT key features and SVM. These key features for modulation classification should have good properties of sensitive with modulation types and insensitive with SNR variation. In this paper, the 4 key features using WT coefficients, which have the property of insensitive to the changing of noise, are selected. The numerical simulations using these features are performed. We investigate the performance of the SVM-DDAG classifier for classifying 8 digitally modulated signals using only 4 WT key features (i.e., 4 level scale), and compare with that of decision tree classifier to adapt the modulation classification module in software radio. Results indicated an overall success rate of 95% at the SNR of 10dB in SVM-DDAG classifier on an AWGN channel.**

Keywords — **Modulation Classification (MC), Wavelet Transformation (WT), Support Vector Machine (SVM), Decision Directed Acyclic Graph (DDAG), Decision Tree (DT).**

1. Introduction

An automatic radio signal classifier finds its use in military and civilian communications applications including signal confirmation, interference identification, spectrum monitoring, signal surveillance, electronic warfare, military threat analysis, electronic counter measure, and software radio system.

Different modulation schemes have the characteristic of different transients in amplitude, frequency or phase. The wavelet transform (WT) is a powerful tool for analyzing non-stationary signals, which include digital communication signals, and the WT magnitude of communication signals vary with modulation types [1]. The WT has capability to extract transient information which can be exploited for modulation classification.

In this paper, we investigate the performances of support vector machine (SVM) classifier with WT key features for 8 types of digital modulated signals, and compare with that of decision tree classifier to adapt the modulation claasification module in software radio.

The paper is organized as follows. In Section 2, the wavelet features for classification are presented. In Section 3, the modulation classification using SVM is presented. In Section 4, we investigate the performance of the SVM classifier using numerical simulations and compare with that of decision tree classifier, and in Section 5, the paper is concluded.

2. Wavelet Key Features Extraction

The key features for modulation classification in pattern recognition approach must be selected. These features should have robust properties of sensitive with modulation types and insensitive with SNR variation [2].

Wavelet key feature extraction is proposed here. The main characteristic of wavelet is that it can provide localized frequency information of a signal, which is very useful for classification. Due to some desirable properties, the wavelet basis constructed by Daubechies became the foundation for the most popular techniques for signal analysis and representation in a wide range of applications. Digital modulated waveform is a cyclostationary signal that contains transients in amplitude, frequency or phase and the WT is quite suitable at extracting transient information. Another attractive feature of WT is that it can be computed using fast algorithm (e.g., Fast WT) and hence allowing identification of modulation types in real time [3].

The continuous wavelet transform (CWT) of a signal $x(t)$ is defined as

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

where the function $\psi(t)$ is called mother wavelet, ψ^* is its complex conjugate, and s is the scaling constant. The baby wavelet $\psi_s(t)$ comes from time-scaling and translation of the mother wavelet.

Different than STFT (Short Time Fourier Transform) in which the window length is fixed, the window size of WT increases as the analyzing frequency decreases [3]. The choice of a mother wavelet depends on its application. Due to its simple form and ease of computation, we selected the Haar wavelet (db1) for modulation classification module of software radio application.

Fig. 1 is the entire WT modulation classification procedure for 8 digital modulated signals. The identifier first finds the magnitude of the WT of an incoming signal without any normalization. After median filtering, we compute the standard deviation of the results. Classification method using these standard deviations of WT coefficients will determine the type of incoming signals.

The WT decomposition process can be iterated with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components as shown in Fig. 2. This is called the WDT (wavelet decomposition tree). In this paper, WDT with scale factor 4 is used for modulation classification.

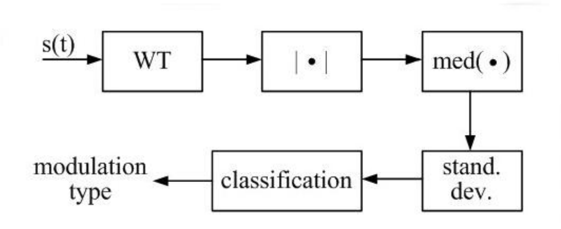

Fig. 1. The procedure of automatic modulation recognition using WT

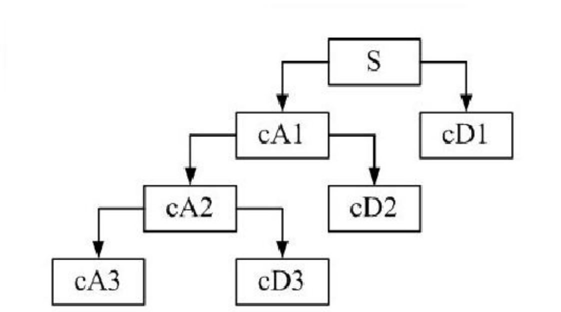

Fig. 2. Wavelet Decomposition Tree

We selected only 4 key features for modulation classification. These key features (i.e. standard deviations of detail coefficients at each level) using Haar WT are shown in Fig. 3a – 3d.

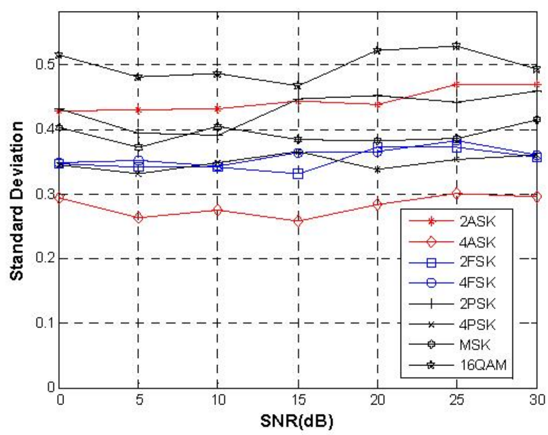

Fig. 3a. Graph of the SNR vs sd_cD1

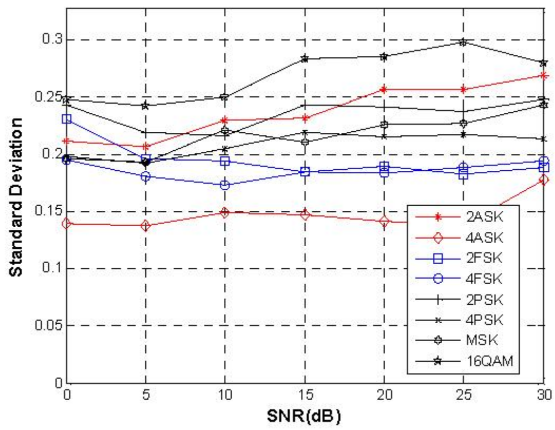

Fig. 3b. Graph of the SNR vs sd_cD2

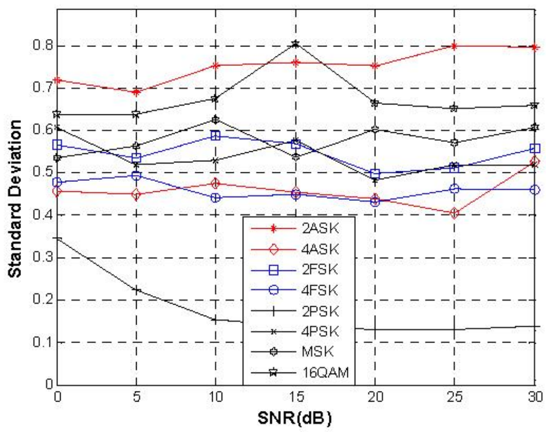

Fig. 3c. Graph of the SNR vs sd_cD3

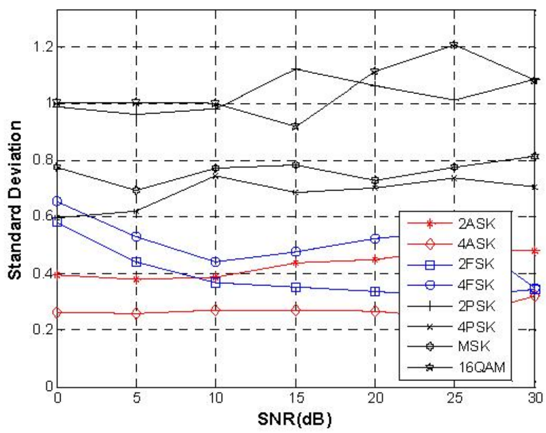

Fig. 3d. Graph of the SNR vs sd_cD4

3. Modulation Classification using SVM

SVM is an empirical modeling algorithm, and is the state-of-the-art for the existing classification methods. The SVM is basically a two-class classifier based on the ideas of "large margin" and "mapping data into a higher dimensional space," and the kernel functions in the SVM.

The first objective of the SVM classification is the maximization of the margin between the two nearest data points belonging to two separate classes. The second objective is to constraint that all data points belong to the right class. It is a two-class solution which can use features in multi dimensions. SVM classifies the points from two linearly separable sets in two classes by solving a quadratic optimization problem in order to find the optimal separating hyperplane between these two classes. This hyperplane maximizes the distance from the convex hulls of each class. These techniques can be extended to the nonlinear cases by embedding the data in a nonlinear space using kernel functions. The robustness of SVM classification originates from the strong fundamentals of statistical learning theory.

In modulation classification using SVM, we used linear, polynomial-of-power-2 and exponential radial basis function (RBF) kernels. One of examples using exponential RBF kernel in SVM classification shows as shown in Fig. 4.

Since SVM is basically a binary classifier, it is not straight forward to apply it to multi-class classification problems. The most typical method for multi-class problem is to classify one class from the other classes (refer 1-v-r), another typical method is to combine all possible two-class (pair wise) classifiers (refer 1-v-1). It's known as 1-v-1 type SVM is superior to 1-v-r with respect to its learning time, but execution time for classification of 1-v-1 is much worse than 1-v-r. The SVM-DDAG (Decision Directed Acyclic Graph) method yields comparable accuracy and memory usage to the other two methods, but yields substantial improvement in both training and evaluation time [4]. We applied SVM-DDAG method using WT for our 8 multi-class modulation classification problem (see Fig. 5).

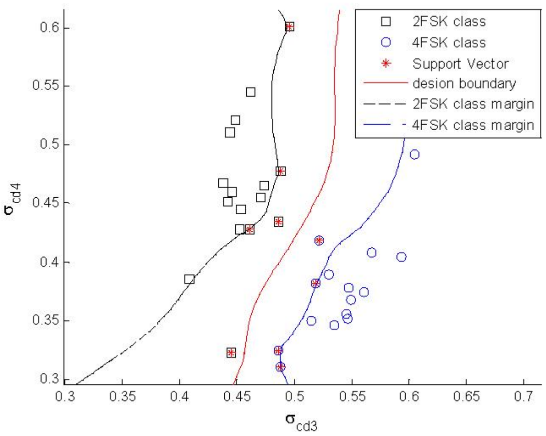

Fig. 4. Classification 2FSK vs 4FSK in SVM

4. Numerical Simulations

In this Section, the performance of the proposed scheme is investigated in the Matlab environment. The 8 digital modulation types (i.e. 2ASK, 4ASK, 2FSK, 4FSK, 2PSK, 4PSK, MSK, and 16QAM) are classified. Digital signals are generated randomly and then modulated into band-limited signal with band-limited AWGN.

The decision tree classifier (DTC) [5], which is known as usually easy to implement and have low complexity, is built for performance comparison of SVM-DDAG classifier. In principle the DTC learning algorithms analyze one feature variable at a time for all the data classes. In Fig. 6, the thresholds (i.e., t1-t7) of decision tree classifier are selected using the Mahalanobis distance [6].

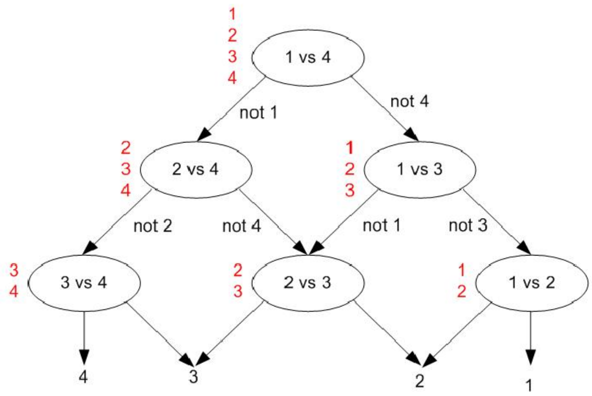

Fig. 5. SVM-DDAG for 4-classes

In numerical simulation, the carrier frequency and sampling rate were chosen to 150 kHz and 1200 kHz, respectively. A random symbol sequence at symbol rate equal to 25k symb/s is used as a modulating signal for digital modulations. So, the number of samples per symbol duration was 48. No a priori knowledge was assumed for the classifier. To distinguish 8 digital modulation types, simulation runs were carried out with 4,096 samples (equivalent to 3.4 ms) at SNR ranging from 0 dB to 30 dB. The probabilities of correct classification (Pcc) obtained from 400 independent ensembles at each SNR in SVM-DDAG classifier are plotted for each modulation types as shown in Fig. 7.

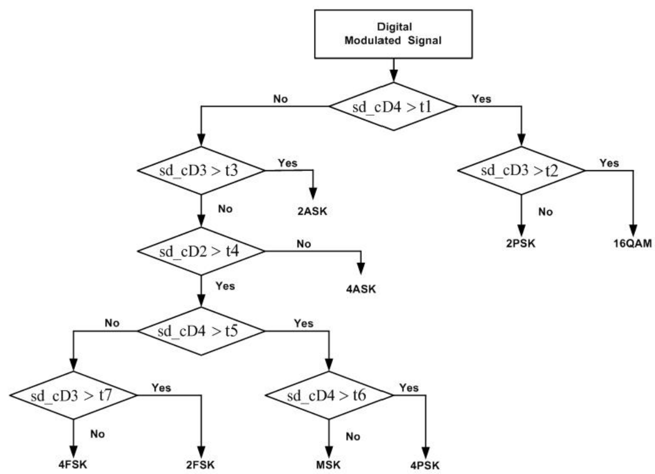

Fig. 6. Flowchart of Decision Tree Classifier

Results indicated an overall success rate of over 90% at the SNR of 10dB in 2 classification schemes as shown in Fig. 8. Especially, it was shown that SVM-DDAG classifier can achieve the good results with high Pcc (i.e., >= 95%) over region of 10dB SNR. Fig. 9 is Pe (Probability Classification

Error) version of log scale for Fig. 8 to show the details of the performance for specific region (i.e., 0-10dB SNR).

The detailed classification results at the SNR of 10dB in 2 classifiers are provided in the confusion matrix as listed in Table 1 – 2. The global Pccs of decision tree classifier and SVM-DDAG classifier are obtained 90.19% and 95.47% at the SNR of 10dB, respectively.

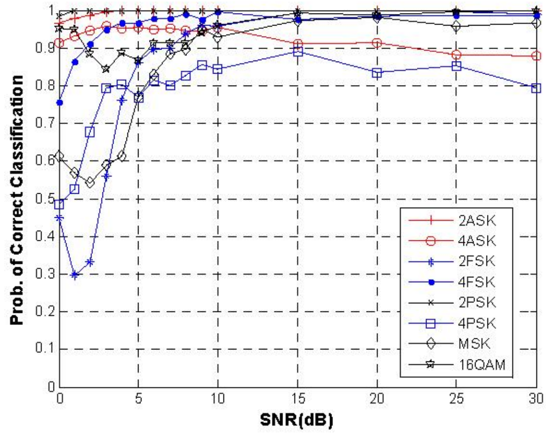

Fig. 7. Pcc of 8 digital modulation types at SNR from 0dB – 30dB in SVM-DDAG

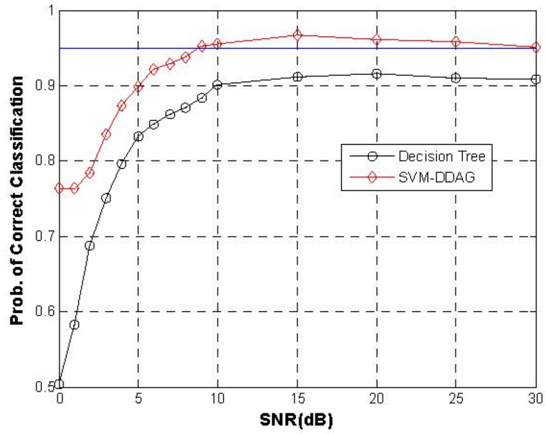

Fig. 8. Pcc of 2 classifiers at SNR from 0dB – 30dB

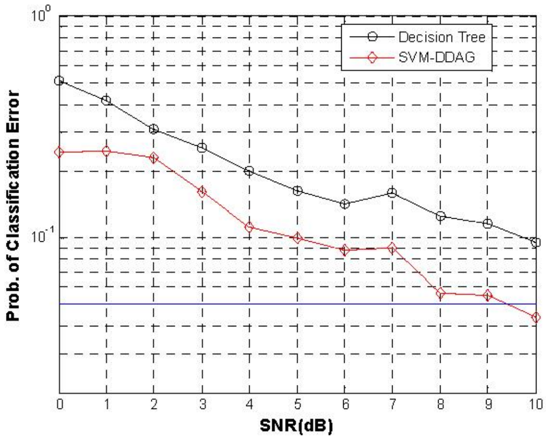

Fig. 9. Pe of 2 classifiers at SNR from 0dB – 10dB

5. Conclusion

In this paper, we proposed a robust SVM-DDAG classifier using 4 WT coefficients capable of recognizing 8 digitally modulated signals without a priori information.

We investigate the performance of the proposed classifier using numerical simulation and compare with that of decision tree classifier. In numerical simulation, 2 classifiers used the only 4 key features using Haar WT magnitude.

Results indicated an overall success rate of over 90% at the SNR of 10dB in 2 classification schemes as shown in Fig. 8. These good results came from the large effects of properties of the WT coefficients, which have the property of insensitive to the changing of noise. Especially, it was shown that SVM-DDAG classifier due to the statistical strong learning theory of SVM and the robust property of WT magnitude for a wide range of SNR can achieve over the 95% of Pcc at the SNR of 10dB.

Table 1. Confusion Matrix of Decision Tree (%)

Actual Modulation	Classified Modulation Type @ SNR = 10dB							
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	MSK	16QAM
2ASK	100							
4ASK		98.25	1.75					
2FSK			97.5	2.25				
4FSK		16.5	0.5	81.75		1.25		
2PSK					99.5	0.5		
4PSK			3.5	1.0		79.5	16.0	
MSK						32.25	67.75	
16QAM	2.25						0.75	97.0

Table 2. Confusion Matrix of SVM-DDAG (%)

Actual Modulation	Classified Modulation Type @ SNR = 10dB							
	2ASK	4ASK	2FSK	4FSK	2PSK	4PSK	MSK	16QAM
2ASK	100							
4ASK		95.5	1.75	2.75				
2FSK		3.5	95.75	0.75				
4FSK			0.5	99.5				
2PSK					100			
4PSK			0.75	9.5		84.25	5.5	
MSK				0.25		7.0	92.75	
16QAM							4.0	96.0

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