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Automatic Modulation Classification using S-transform based Features

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***Abstract*—Automatic Modulation Classification plays a significant role in Cognitive Radio to identify the modulation format of the primary user. In this paper, we present the Stockwell transform (S-transform) based features extraction for classification of different digital modulation schemes using different classifiers such as Neural Network (NN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Naive Bayes (NB), k-Nearest Neighbor (k-NN). The S - transform provides time-frequency or spatial-frequency localization of a signal. This property of S-transform gives good discriminant features for different modulation schemes. Two simple features i.e., energy and entropy are used for classification. Different modulation schemes i.e., BPSK, QPSK, FSK and MSK are used for classification. The results are compared with wavelet transform based features using probability of correct classification, performance matrix including classification accuracy and computational complexity (time) for SNR range varying from 0 to 20 dB. Based upon the results, we found that S-transform based features outperform wavelet transform based features with better classification accuracy and less computational complexity.**

I. 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, cognitive radio [1], [2]. Automatic Modulation Classification (AMC) is an indispensable step between signal detection and demodulation. These classification techniques can be classified into two categories: likelihood-based (LB) decision-theoretic method and feature-based (FB) pattern recognition (PR) method. Decision-theoretic methods use statistical properties of the received signal to form an estimate based on the maximum likelihood (ML) [3]. These methods are computationally complex and difficult to implement. Furthermore, these methods are not robust with model mismatch such as phase and frequency offsets, residual channel effects and timing errors [4]. Whereas, pattern recognition algorithms exploit the characteristic of the received signal to make decision. Although, the performance of feature based (FB) methods may not be optimal, they are simple to implement, with near-optimal performance when designed properly. These methods are mainly consist of two stages: First, features of the received signals are extracted and then in the second stage the classifier is used to classify the features.

In literature, various types of features have been used in AMC, e.g., higher order cumulants and moments, wavelet transform, cyclo-stationarity, instantaneous amplitude, phase, and frequency features [5]. The higher order moments and cumulants are used as features for AMC in [6], [7], [8] and [9]. The 4^{th} and 6^{th} order cumulants of received modulated signal are used as features for classification in [10], [11]. In [12], the digital modulation schemes are classified by higher order statistical moments of wavelet transform and fractional fourier transform using principal component analysis. In [13], the modulated signal constellation shape is used to recognize digital modulation scheme. Higher order spectra are used as features in [14]. The N^{th} power non linear features in fourier domain are utilized in AMC without reconstructing the signal completely [15]. Expectation maximization is used to perform blind modulation classification in fading channel [16]. In [17], probability distribution distance function called as Kuiper and Kolmogorav-smirnov distances are proposed for modulation classification. Using Bayesian criteria, optimal discriminant functions based on sampled distribution distance are discussed for modulation type classification in [18]. In [19], cyclostationarity property of the modulated signals is exploited for modulation classification.

Transform domain features are often used in different classifiers for modulation schemes classification. In past, these features are extracted by transforming the signal to Fourier or Wavelet domains. Recently, S-transform is widely used to classify power quality disturbances [20]–[23]. S-transform is a hybrid form of the short-time Fourier transform and Wavelet transform (WT) which has the property to preserve the phase of the signals as well as other key signal characteristics [24]. The S - transform provides time-frequency or spatial-frequency localization of a signal [24]. The peak of the time-frequency representation helps in estimating the instantaneous information bearing phase. This property of S-transform allows to find good discriminant features for different modulation schemes. Hence, this key property of S-transform inspires us to use it for features extraction of the received signal whose modulation is required to be recognized. To evaluate the performance of the proposed method, we compared the results with the WT based feature results using different classifiers i.e., NN, NB, k-NN, SVM and LDA.

The rest of the paper is organized as follows: Section II presents background and signal model. It reviews the basic concepts and properties of S-transform. In Section III, the proposed method is described. In Section IV, performance results and discussion are explained in details. Finally, the conclusions of the paper are reported in Section V.

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II. Background and Signal Model

A. S-transform Analysis

The Short Time Fourier Transform (STFT) provides low resolution whereas Continuous Wavelet Transform (CWT) does not contain phase information. These deficiencies of STFT and CWT led to the development of the S-transform, which has the property of retaining the absolute phase information, while preserving a good time-frequency resolution for all frequencies [24]. The S-transform is a spectral localization technique which is very much similar to the WT and STFT using variable window. It can be considered as a special case of the STFT by replacing the window function with a frequency-dependent Gaussian window. In the S-transform domain the Gaussian window is scaled so that the window width is inversely proportional to the frequency, and its height is scaled proportional to the frequency. This behaviour of the window scaling, produces good time resolution for high-frequency components and good frequency resolution for low-frequency components. S-transform can also be derived from the WT with a specific mother wavelet multiplied by the phase factor which gives time frequency resolution identical to wavelet transform. S-transform is well known because of its local spectral phase properties and hence emerged with numerous applications in time frequency representation [24].

Let, a time series **x**(t), then the S-transform of **x**(t) is given by

$$S(\tau, f) = \int_{-\infty}^{\infty} \mathbf{x}(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-j2\pi f t} dt. \tag{1}$$

where, $\mathbf{u}(t) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}}$ is the gaussian window function, τ is time of spectral localization and f is Fourier frequency. So, the S-transform can be generalized form of STFT with the gaussian window [24]. It is possible to combine the time domain and frequency domain by using the Gaussian window. In S-transform, Gaussian window is considered because of the following reasons:

- No side lobes exist in a Gaussian function
- Gaussian window is symmetric both in time and frequency i.e., Fourier transform of a Gaussian is Gaussian.

S-transform can give better frequency resolution for lower frequency, if the window is wider in time domain. Whereas, it results better time resolution for higher frequency, if the window is narrower. Hence, the window spread depends on f.

Similarly S-transform can be derived by Wavelet domain [25] as follows

$$S(\tau, f) = e^{-j2\pi f \tau} G(\tau, d) \tag{2}$$

Where $G(\tau, d)$ is the mother wavelet and is given by

$$g(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-j2\pi f t} \tag{3}$$

Scale parameter d is the inverse of the frequency f. It is noted that (3) does not have zero mean so (2) is not absolutely a CWT. So the S-transform is given by [25]

$$S(\tau, f) = \int_{-\infty}^{\infty} \mathbf{x}(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-j2\pi f t} dt. \tag{4}$$

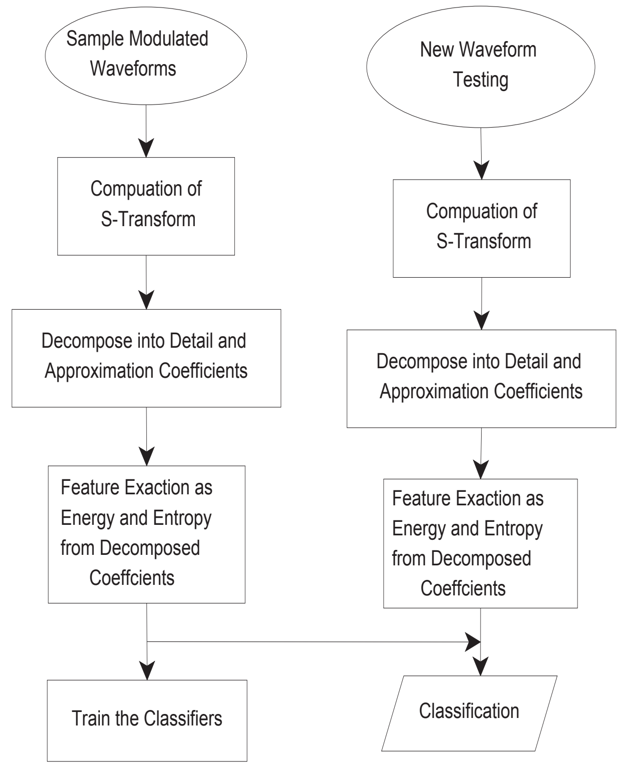

Fig. 1. Flow chart of Proposed Method

III. Proposed Method

In this paper, the proposed classification technique consists of two stages: feature extraction and classification using different classifiers.

A. Feature Extraction

In pattern recognition methods, feature extraction is the most essential component as the classifier's performance depends on the proper design of the signal features [26]. Hence, it is important to choose optimum features size with maximum information. So, a feature extractor is used for reducing the pattern vector or the original signal to a lower dimension, which accommodates the most important information from the original vector [27]. In this paper, we discuss about the S-transform based feature extraction. As, the S-transform has varying window it overcomes the defect of fixed height and width of STFT window. The Fourier transform can not position time and frequency at the same time. The features extracted from the S-transform contain time domain, frequency domain as well as phase information, and therefore are more robust with respect to modulation classification than those based on Fourier transform and Wavelet transform. So, there is a need to wisely choose the simple features which can provide good classification performance. In this paper, we propose to calculate S-transform of the received modulated signal and perform wavelet decomposition of the transformed signal using Daubechies family wavelet at multiple level. BY wavelet decomposition, approximation and detail coefficients are calculated. In this paper, we have used simple energy and entropy as features calculated from these decomposed

TABLE I. CONFUSION MATRIX FOR DIFFERENT CLASSIFIER USING S-TRANSFORM FEATURES

Classifier	Modulation	SNR=0 dB				SNR=5 dB				SNR=10 dB				SNR=15 dB				SNR=20 dB			
Neural Network	BPSK	0	96	4	0	4	4	32	60	60	0	2	38	90	0	2	8	94	0	0	6
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	92	8	0	0	22	64	14	0	4	82	14	0	0	90	10	0	0	98	2
	MSK	0	94	0	6	0	12	0	88	0	0	0	100	0	0	0	100	0	0	0	100
Naive Bayes	BPSK	0	98	2	0	0	0	100	0	0	0	8	92	100	0	0	0	100	0	0	0
	QPSK	0	0	100	0	0	98	2	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	92	8	0	0	8	92	0	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	0	100	0	0	0	100	0	0	0	100	0	0	0	4	96	0	0	0	100
Linear Discriminant Analysis	BPSK	0	100	0	0	0	0	100	0	4	0	0	96	92	0	0	8	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	100	0	0	0	68	32	0	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	100	0	0	0	0	100	0	0	0	94	6	0	0	0	100	0	0	0	100
K-Nearest Neighbor	BPSK	0	100	0	0	0	0	100	0	0	0	0	100	100	0	0	0	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	100	0	0	0	50	50	0	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	100	0	0	0	0	100	0	0	0	100	0	0	0	20	80	0	0	0	100
Support Vector Machine (Default Kernel)	BPSK	0	100	0	0	0	0	16	84	18	0	0	82	92	0	0	8	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	100	0	0	0	46	52	2	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	100	0	0	0	0	4	96	0	0	0	100	0	0	0	100	0	0	0	100

coefficients. These extracted features are used by various classification algorithms to recognize the modulation type.

B. Classifiers

The role of classifier is to identify the type of intercepted signals. Different classifiers have been proposed in the literature in AMC. In modulation classification methods, the decision making can be implemented by two ways i.e., decision theoretic [26], [28], [29] and pattern recognition. Pattern recognition classification methods are based on NNs [26], [30], [31] and SVMs [32], [33] or combination of more than one Artificial Intelligence (AI) technique to optimize the solution [30]. The main aspect of utilizing PR methods is to enhance the classification rate at low SNR. It is important to find a suitable combination of classifier and features to get high classification accuracy at very less computational time or cost. In this paper, we have made a rigorous study to find suitable combination of classifier and S-transform features. So, we have tested our proposed features for AMC with different classifiers i.e., NN, NB, k-NN, LDA and SVM. Details of these classifiers are given in [34]. Flowchart of our proposed method is shown in figure 1.

IV. RESULTS AND DISCUSSIONS

In this paper, S-transform based features have been proposed for classification of different digital modulation schemes including BPSK, QPSK, MSK and FSK. Effectiveness of our proposed method is tested using different classifiers i.e., NN, NB, LDA, SVM, k-NN etc in performance matrix as shown in Table I. Table I shows the confusion matrix for different modulation schemes using S-transform features at different SNRs. The diagonal elements of confusion matrix represent number of correct classification and off diagonal entries denote number of misclassification. 100 signals generated for different modulation schemes at each SNR to calculate the probability of classification. 2000 symbols have been used for each modulation schemes. In the proposed method, we decomposed the S-transform coefficients into 5 levels (approximation or

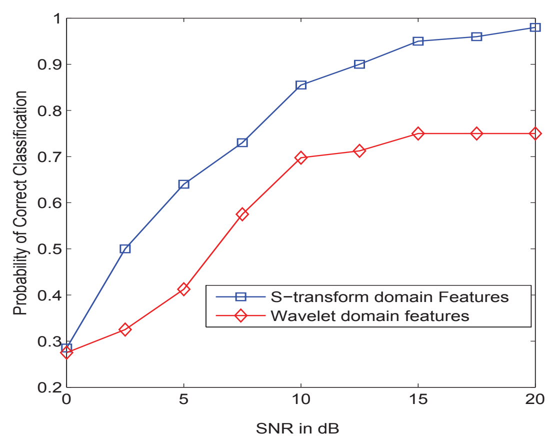

Fig. 2. Comparison of Probability of Correct Classification of WT based features and the proposed method of S-transform based features using Neural network based classifiers

detail coefficients) using 'db6' wavelet. Energy and entropy have been calculated from which features of the received signal are extracted. These S-transform based extracted features are then used for training the different classifiers for identification of modulation type. Figure 2 shows the probability of correct classification for S-transform based features and wavelet based features. Wavelet energy is used as feature for comparison with S-transform features. Probability of correct classification shown in figure is the average of probability of correct classification of all modulation schemes using neural network classifier. The reason for choosing NN is that it is taking very less time for S-transform based features as compare to others as shown in Table III. It is evident from Figure 2 that AMC based on S-transform outperforms wavelet based classifiers. Table II shows the confusion matrix for wavelet transform based features. It is clear from Table I and Table II that S-transform based features perform better than wavelet based features in terms of probability of correct classification as well as in

TABLE II. CONFUSION MATRIX FOR DIFFERENT CLASSIFIER USING WAVELET FEATURES

Classifier	Modulation	SNR=0 dB				SNR=5 dB				SNR=10 dB				SNR=15 dB				SNR=20 dB			
Neural Network	BPSK	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0
	QPSK	1	0	99	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0
	FSK	0	20	10	70	0	35	65	0	0	0	80	20	0	0	100	0	0	0	100	0
	MSK	0	0	100	0	100	0	0	0	1	0	0	99	0	0	0	100	0	0	0	100
Naive Bayes Neighbor	BPSK	0	5	95	0	0	100	0	0	0	100	0	0	0	100	0	0	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	99	1	0	0	100	0	0	0	91	0	9	0	0	0	100	0	0	0	100
Linear Discriminant Analysis	BPSK	0	100	0	0	1	99	0	0	100	0	0	0	100	0	0	0	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	100	0	0	82	18	0	0	0	0	0	100	0	0	0	100	0	0	0	100
K-Nearest	BPSK	0	100	0	0	40	60	0	0	100	0	0	0	100	0	0	0	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	100	0	0	90	10	0	0	100	0	0	0	0	0	100	0	0	0	100	0
	MSK	0	100	0	0	2	98	0	0	100	0	0	0	30	0	0	70	0	0	0	100
Support Vector Machine (Default Kernel)	BPSK	0	100	0	0	1	59	0	40	100	0	0	0	100	0	0	0	100	0	0	0
	QPSK	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0	0	100	0	0
	FSK	0	100	0	0	0	13	87	0	0	0	100	0	0	0	100	0	0	0	100	0
	MSK	0	100	0	0	0	100	0	0	0	0	0	100	0	0	0	100	0	0	0	100

TABLE III. COMPUTATIONAL TIME (CT) COMPARISON BETWEEN WAVELET FEATURES AND S-TRANSFORM (ST) FEATURES

Classifier	WT CT(in sec.)	ST CT(in sec.)
Naive Bayes	0.1899884	0.040596
Support Vector Machine	3.474536	0.092838
Linear Discriminant Analysis	0.1317101	0.040651
K-Nearest Neighbor	0.1295188	0.055543
Neural Network	0.477	0.008071

computational time as shown in Table III. Computational Time (CT) in Table III represents the testing time of classifier to identify the modulation scheme. It is noted from the simulation results that the recommended method provides more accurate recognition of modulation scheme as compared to the earlier Wavelet domain transform.

V. CONCLUSION

In this paper, we have proposed a new feature extraction method based on S-transform. The S-transform provides good time-frequency resolution of a signal by preserving the phase information. Energy and Entropy are used as features extracted from the decomposed coefficients of S-transform. We have evaluated the performance of S-transform based features using different classifiers i.e. NN, NB, LDA, k-NN, SVMs etc. Four modulation schemes i.e., BPSK, QPSK, FSK and MSK have been classified at different SNR ranging from 0 to 20 dB. We have compared our results of S-transform features with the wavelet based features. The performance of our proposed method is evaluated using confusion matrix and computational time. Simulation results show that our S-transform based features outperforms wavelet based features both in terms of probability of correct classification as well in computational time.

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