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Automatic Digital Modulation Recognition Based on Novel Features and Support Vector Machine

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***Abstract*— In this paper a novel algorithm for automatic modulation recognition (AMR) based on pattern recognition approach is proposed. The main focus here remains on feature extraction block and the novel features are introduced in order to identify digital modulation schemes. The modulation types include: BASK, BFSK, BPSK, 4-ASK, 4-FSK, QPSK, and 16-QAM and the channel model is considered as an AWGN channel. The features are extracted from the received signal that is considered in the time, frequency and wavelet domains. Also, to overcome the multiclass problem, a hierarchical structure is investigated based on binary support vector machine (SVM). The simulations demonstrate superior capabilities of the proposed features in accurately separating digitally modulated signals in an extremely noisy environment with very low SNR values. Accordingly, the minimum SNR for the perfect identification is proven to be -5 dB, and a final accuracy percentage of 98.15 has been obtained in -10 dB.**

Keywords- Automatic Modulation Recognition (AMR), Robust Features, Low SNRs, Pattern Recognition, Support Vector Machine (SVM)

I. INTRODUCTION

Nowadays with developing of modern communications systems, the AMR algorithm remarkably plays a significant role in multiple applications. In this matter, various academic and military research institutes have concentrated on this research area for developing AMR algorithms in order to accurately identify the modulation type of the received unknown RF signals. The AMR techniques have wide range of applications in the civilian and military purposes. For Instance, the AMR methods can be employed in spectrum surveillance and management, interference recognition and monitoring, electronic counter measure and so on. Due to its importance, lots of studies have been accomplished and various algorithms have been introduced using diverse techniques in this regard and attempted to achieve higher accuracy in the lower values of SNRs as much as possible.

All of the developed AMR algorithms can be categorized into two major principles; the decision theory and the pattern recognition techniques. In the methods developed based on decision theory, AMR problem is mostly formulated using probabilistic and hypothesis testing arguments. In [1-4], an AMR algorithm is developed based on likelihood functions. Although this method is able to find optimal solution, it has high computational complexities. Azzouz and Nandi also proposed the feature based algorithms based on the decision theoretic approach in [5-6]. Their method has low computational complexities in comparison with the maximum likelihood technique; however, it requires to determine specific thresholds for identification of considered modulation types by decision tree. Several papers [7], [8] and [9] have been published, each of which has used a similar method for the AMR problem.

In the recent years, due to the high computational complexity, specifying appropriate threshold values and the other difficulties of decision theoretic approaches, AMR algorithms have been mostly implemented based on pattern recognition approaches providing more flexibilities. These algorithms consist of two general modules including feature extraction and classification blocks. Recently, numerous AMR techniques have been proposed based on pattern recognition approach with different classification structures using Artificial Neural Network (ANN) [10-15] and SVM classifiers [16-19]. In these studies, various types of features such as statistical features including higher order statistics [11], [12], [17], [18], spectral features including instantaneous amplitude, frequency and phase [12], [15] and wavelet-based features [14], [19], [20], have been employed.

In this paper, we propose a structure using pattern recognition approach based on novel features in order to identify the digital modulation type of the unknown received signals. Fig. 1 shows the general block scheme of the proposed AMR model. The received modulated signal is modeled as the following

$$z(\mathrm{t}) = \tilde{\mathrm{s}}(\mathrm{t}) e^{j(2\pi \mathrm{f_c} \mathrm{t} + \varphi_c)} + n(\mathrm{t}) \quad (1)$$

where f_c is the carrier frequency, φ_c is the carrier phase, and *n(t)* denotes the complex additive white Gaussian noise. Also, $\tilde{\mathrm{s}}(\mathrm{t})$ is the baseband complex envelope of real signal *s(t)* defined as

$$\tilde{\mathrm{s}}(\mathrm{t}) = a(\mathrm{t}) e^{j[2\pi \mathrm{f(t)} \mathrm{t} + \varphi(\mathrm{t})]} \quad (2)$$

where *a(t)*, *f(t)* and *φ(t)* are the instantaneous amplitude, frequency and phase of the signal, respectively.

As it is shown in Fig.1, after receiving the intercepted modulated signal, pre-processing block prepares it for the next block by performing required pre-processing operations such as the amplitude normalization, the filtering operation, the instantaneous amplitude, frequency and phase extraction, and the median filtering.

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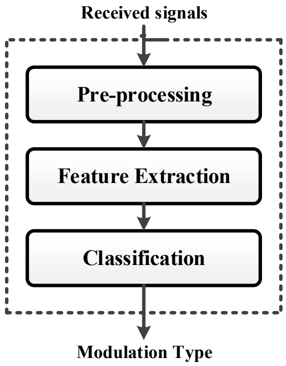

Fig. 1. General block scheme of proposed AMR algorithm

The main contribution of this paper is on the feature extraction block, since extracting beneficial data from the time, frequency and wavelet domains of the normalized received signal plays essential role in the correctly discriminating digital modulation types in the very low SNR scenarios. Accordingly, several novel features are introduced including the novel wavelet-based features obtained based on our previous proposed structure in [21]. Also some features investigated in the previous works are modified and used here to discriminate the mentioned modulation types. The feature extraction block is explained in detail in section II. In the next block, modulation types of the received signals are identified using a binary tree structure based on SVM classifiers which is introduced in section III. In section IV, the simulation results of the proposed method are compared to the accuracy rates obtained by applying features to a SVM structure developed based on a well-known approach named one against one (OAO) method. The comparison shows that the proposed binary tree structure not only has higher accuracy but also has considerably less complexity compared to the OAO structure. The simulation results demonstrate that the investigated algorithm is superior to the previous ones in number of aspects including accuracy and robustness. Finally, section V provides the conclusion.

II. FEATURE EXTRACTION

The feature extraction is a crucial step of any AMR algorithms developed by the pattern recognition approach. In this step, some measurable quantities called features are extracted from the received modulated signals in order to be used for the classification step. These features should adequately describe the characteristics of the digitally modulated signals and be tolerant to the channel noise and input variation. In this section, we introduce some novel features which can be categorized into two parts: the temporal and spectral-based features, and the wavelet-based features which are evaluated in the following section. Furthermore, the simulation results related to different features have been presented in Fig. 2. These results have been obtained by analyzing the proposed features in order to show their variations against the channel noise. Also, it is worth mentioning that in the diagrams shown in Fig. 2, each point represents the average value of the related feature for 1000 realizations of the corresponding modulation type at each SNR value.

A. Temporal and Spectoral Features

In this part, four different features based on the hidden information in spectrum, instantaneous amplitude, frequency and phase of the received signal are introduced. Three of these features are extracted from the time domain and one of them is related to the frequency domain.

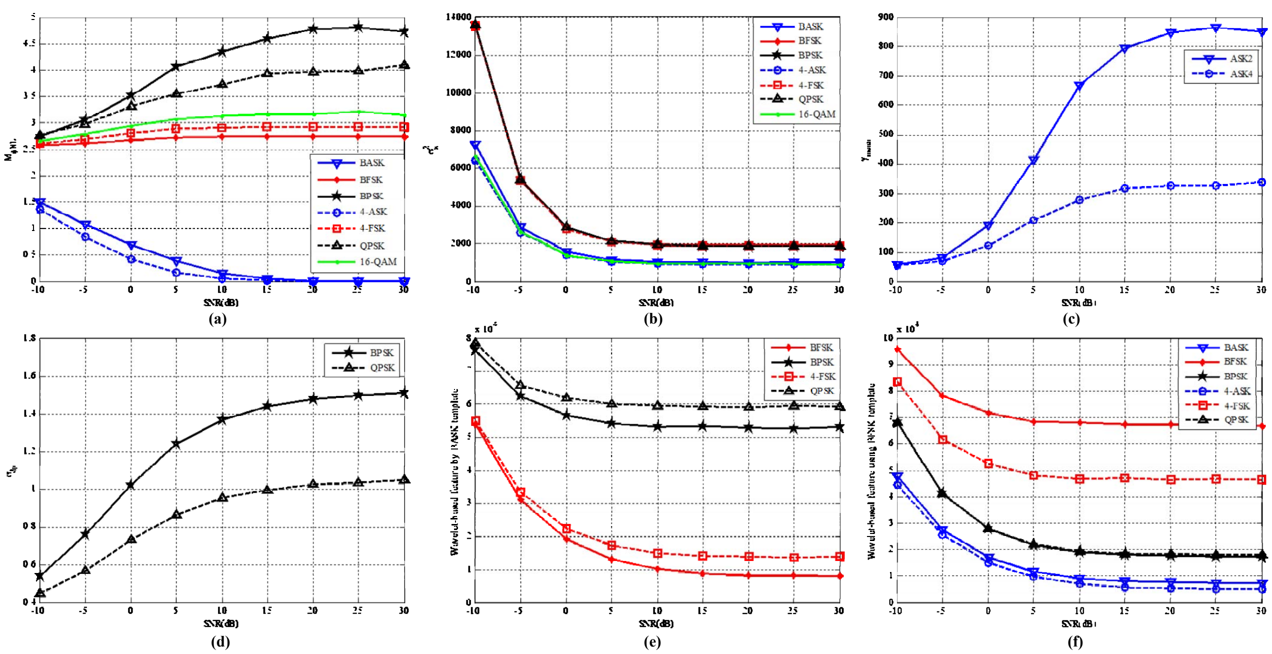

Fig. 2. Values of the proposed features versus SNR

A.1. Second-order moment of non-linear component of the instantaneous phase

$$M_{\varphi_{NL}} = \frac{1}{N_s}\sum_{i=1}^{N_s}\varphi_{NL}^2(i) \quad (3)$$

where φ_{NL} is the normalized-centered non-linear component of the instantaneous phase given by $\varphi_{NL}(\mathrm{i}) = \varphi(\mathrm{i})/\overline{\varphi} - 1$ in which $\varphi(i)$ and $\overline{\varphi}$ are the instantaneous phase and the mean phase values, respectively. Also, N_s is the number of samples of the intercepted received signal. Since there is no information in the instantaneous phase of ASK modulated signals, the proposed feature would be able to distinguish between ASK and the other modulations. Simulation results obtained by applying this feature to the received signals shows that ASK modulation has the lowest value compared to the others (Fig. 2(a)).

A.2. Spectrum based feature

$$\sigma_Z^2 = \frac{1}{N_s}\sum_{i=1}^{N_s}\left(Z(i) - \frac{1}{N_s}\sum_{i=1}^{N_s}Z(i)\right)^2 \quad (4)$$

where $Z(i)$ is Fourier transform of the analytic representation of the received signal, and N_s denotes the number of samples in the considered frame of the intercepted signal. As it can be seen in Fig. 2(b), this novel feature is proposed in order to identify modulations with no amplitude information (FSK and PSK) from ASK and QAM.

A.3. mean value of the power spectral density of the normalized-centered instantaneous amplitude of the intercepted signal segment

$$\begin{aligned}\gamma_{mean} &= E\{|DFT(a_{cn})|^2\} \\ &= \frac{1}{N_s}\sum_{i=1}^{N_s}|\mathrm{A}_{cn}(\mathrm{i})|^2\end{aligned} \quad (5)$$

where $A_{cn}=DFT(a_{cn})$, and a_{cn} is the value of the normalized-centered instantaneous amplitude at time instants $t=i/f_s$, ($i=1,2,\ldots,N_s$) and it is defined by

$$a_{cn}(\mathrm{i}) = \frac{a(\mathrm{i})}{m_a} - 1 \quad (6)$$

where m_a is the average value of the instantaneous amplitude evaluated over one segment given by

$$m_a = \frac{1}{N_s}\sum_{i=1}^{N_s}a(\mathrm{i}) \quad (7)$$

where N_s is the number of samples in each frame, and a is the instantaneous amplitude of the intercepted signal. It is demonstrated that the presented feature is a suitable parameter to distinguish between BASK and 4-ASK modulations (Fig. 2(c)).

A.4. Standard deviation of the normalized-centered non-linear component of the direct instantaneous phase

$$\sigma_{dp} = \sqrt{\frac{1}{N_s}\left(\sum_{i=1}^{N_s}\varphi_{NL}^2(i)\right) - \left(\frac{1}{N_s}\sum_{i=1}^{N_s}\varphi_{NL}(i)\right)^2} \quad (8)$$

Similar to (3), φ_{NL} is the normalized-centered non-linear component of the instantaneous phase, and N_s is the number of samples in the frame taken into consideration. This feature is a modified version of the proposed algorithm investigated by Azzouz and Nandi [5]. Fig. 2(d) shows that this feature is suitable for recognizing BPSK from QPSK modulations. The modification is applied using the median filter with the suitable window size in the extraction procedure of the non-linear component of the instantaneous phase.

B. Wavelet Domain Features

The wavelet transform provides an environment in which the signals can be analyzed at different frequencies with different resolutions. Hence, some particular features of signals is only revealed in this domain, but otherwise cannot be extracted using other forms of Transforms. In this paper, the continuous wavelet transform (CWT) is used for extracting separable features from the received signals. Continuous wavelet transform is defined as

$$CWT(a,\tau) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{+\infty}x(\mathrm{t})\psi^*\left(\frac{t-\tau}{a}\right)dt \quad (9)$$

where $\psi(t)$ denotes the mother wavelet, ψ^* is its complex conjugate, $a\neq 0$ is the scale and τ is the translation variable. Moreover, Haar function, which is the simplest wavelet function, is chosen as the mother wavelet for computing CWT.

In the proposed algorithm, we extract two novel features from the digitally modulated signals considered in the wavelet domain. we have shown in [21] that these features are extremely robust against the channel noise. Besides, the structure for extracting these two following features have been demonstrated in details in [21].

B.1. Comparing CWT of the received signal with BASK Template

According to the structure proposed in [21], this feature is calculated using processing of the output signal generated by cross-correlation of the received signal with BASK template in the wavelet domain. This feature is used in order to discriminate between FSK and PSK modulation types. The variation of the values of the proposed feature versus the channel noise is shown in Fig. 2(e). It can be inferred from Fig. 2(e) that FSK and PSK modulation types are perfectly discriminated from each other.

B.2. Comparing CWT of the received signal with BFSK Template

In this case, cross-correlation of the received signal with BFSK template is computed in the wavelet domain. The value of this feature is obtained by calculating the mean of the output signal resulted after comparing it with BFSK template. The steps of the algorithm for extracting the proposed feature could be found in [21]. Fig. 2(f) illustrates the diagram of values of this feature against the different values of SNRs. As it is shown in Fig. 2(f), the proposed feature is excellently differentiates between ASK, FSK, and PSK modulation types.

III. CLASSIFIER

Data classification is the common function of machine learning techniques. SVM is a group of the supervised learning techniques in the field of machine learning used for the pattern classification and regression. SVMs belong to a set of generalized linear classifiers and they are basically utilized to solve the two-group classification problems. In the recent years, SVM has been received increasing interests in many applications due to its high generalization capabilities [22].

In the linear SVM, suppose that we have a data set D including the *n* training points defined as

$$D=\{(x_i,y_i)\,|\,x_i\in\mathbb{R}^P,y_i\in\{-1,1\}\}_{i=1}^{n} \tag{10}$$

where each input x_i is a P-dimensional vector belonged one of two classes $y_i=-1$ or $+1$. The aim of SVM is to find a separator hyperplane with the maximum margin separating between these two classes. This hyperplane can be defined as

$$w.x+b=0 \tag{11}$$

where w is normal to the hyperplane and $b/\|w\|$ is the perpendicular distance from the hyperplane to the origin.

The support vectors are the training data points which are closest to the separating hyperplane. The objective is to be looking for the values for *b* and *w* by which the parallel planes have the maximum distance from each other. These plates that the support vectors lie on can be described by the following equations:

$$w.x+b=1 \tag{12}$$

$$w.x+b=-1 \tag{13}$$

If the training data are linearly separable, we can consider two parallel plates in the support vector points and the problem would be to maximize the distance between these plates. Based on the geometric relations, the margin is equal to $2/\|w\|$. Hence, in order to maximize the margin, we can minimize $\|w\|$. On the other hand, in order to prevent the entry of the points to the margin, the input data have to satisfy the following equation.

$$y_i(w.x_i+b)\geq 1 \tag{14}$$

Hence, an optimization problem is obtained as:

$$\min\|w\| \quad s.t.\ \forall i \quad y_i(w.x_i+b)-1\geq 0 \tag{15}$$

Minimizing $\|w\|$ is equivalent to Minimizing $\|w\|^2/2$. Therefore, the problem is

$$\min\frac{1}{2}\|w\|^2 \quad s.t.\ \forall i \quad y_i(w.x_i+b)-1\geq 0 \tag{16}$$

This is a Quadratic Programming (QP) optimization problem. Using the Lagrange multipliers, *i=1,2,…,P*, the problem can be described as

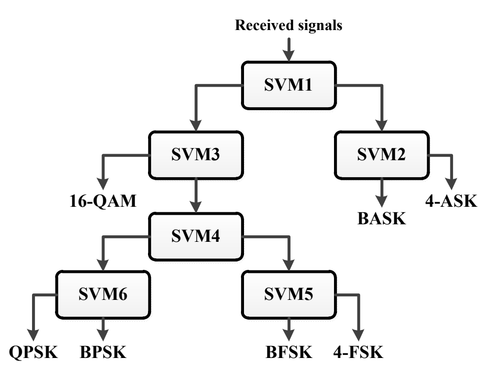

Fig. 3. Proposed hierarchical classifier

Table 1. Characteristics of binary SVMs used in proposed classifier

Binary SVMs	Characteristics of SVMs			
	Applied Feature(s)	Input signals	Output Classes	
			C1	C2
SVM1	$M_{\phi_{NL}}$	BASK, BFSK, BPSK, 4-ASK, 4-FSK, QPSK, 16QAM	BFSK, BPSK, 4-FSK, QPSK, 16QAM	BASK, 4-ASK
SVM2	γ_{mean}	BASK, 4-ASK	BASK	4-ASK
SVM3		BFSK, BPSK, 4-FSK, QPSK, 16QAM	16QAM	BFSK, BPSK, 4-FSK, QPAK
SVM4	Wavelet-based features using BASK & BFSK templates	BFSK, BPSK, 4-FSK, QPAK	BFSK, 4-FSK	BPSK, QPSK
SVM5	Wavelet-based features using BFSK template	BFSK, 4-FSK	BFSK	4-FSK
SVM6	σ_{dp}	BPSK, QPSK	BPSK	QPSK

$$\min\left\{\frac{1}{2}\|w\|^2-\sum_{i=1}^{n}\alpha_i\,[y_i\,(w.x_i-b)-1]\right\} \tag{17}$$

This minimization problem is solved with respect to *w* and *b*. The answer is evaluated by the linear combination of the training vectors as following

$$w=\sum_{i=1}^{n}\alpha_i y_i x_i \tag{18}$$

It can be demonstrated that the dual of the SVM problem is simplified to the following optimization:

$$\begin{aligned}L(\alpha)&=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j x_i^T x_j\\&=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j k(x_i,x_j)\end{aligned} \tag{19}$$

where k denotes Gaussian kernel function, $\alpha_i\geq 0$, and *i=1,…,n*.

Since SVM basically is a two-class classifier and the considered issue in this paper is a multiclass problem, we have proposed a hierarchical structure in order to identify the mentioned digitally modulated signals as it is shown in Fig. 3. It can be inferred from Fig. 3 that the proposed structure is indeed the combination of the decision tree and the binary SVM classifiers. In the each node of the structure, there is a two-class SVM dividing the inputs into two classes. The mentioned tree classifier has been presented based on the diagrams in section II represented the simulation results for the each proposed feature. The diagrams illustrate capability of the each feature in order to classify the supposed digital modulations. These features are employed in the binary SVMs of the investigated classifier depending on what type of the modulations considered to be classified in the each SVM. Table 1 shows the characteristics of the SVMs including the utilized feature(s), the input signals and the output classes to be discriminated.

Additionally, in order to compare the accuracy of the proposed tree scheme to the well-known approaches, we have assigned the proposed features to the structure implemented by OAO approach in order to compare its results to the binary tree structure. Fig. 4 shows the simulation results of this comparison. The accuracy diagrams of these two classifier schemes demonstrate that

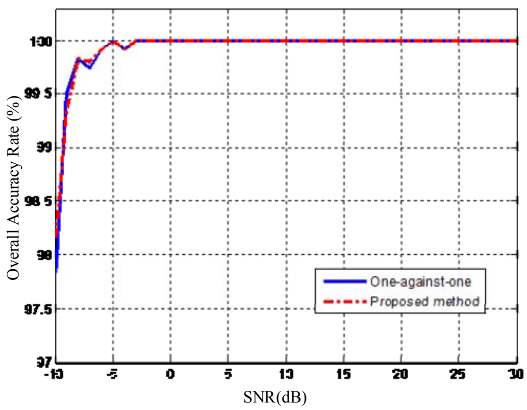

Fig. 4. Average accuracy rate of proposed AMR algorithm using two classifier structures versus SNR values

they have approximately equivalent accuracy in this regard. It can be seen from the presented diagram that the tree classifier in very low SNRs except the values between -8 and -9 dB, even has higher accuracy rate in comparison with the OAO approach. Besides, the hierarchical classifier has considerably low complexity compared to the structure of the OAO approach. Referring to Fig. 4, the number of the required SVMs in the proposed tree scheme for recognition of 7 different modulation types is equal to 6 while the OAO approach needs $7(7-1)/2 = 21$ SVMs.

IV. SIMULATION RESULTS AND PERFORMANCE EVALUAION

In this section, we have evaluated the performance of the proposed algorithm developed in order to identify the supposed digitally modulated signals in the low SNR values. The modulation schemes considered in this work include: BASK, BFSK, BPSK, 4-ASK, 4-FSK, QPSK and 16-QAM. These signals have been implemented in MATLAB software environment in a condition in which the carrier frequency is 150 kHz, the sampling rate is 1.2 MHz and the symbol rate is equal to 12.5 kHz. Moreover, the CWT of signals in the related features is computed using Haar function with 64 scale values. After passing the generated signals through the AWGN channel, the corrupted signals have been assigned to the proposed algorithm in order to extract the key features. We have randomly generated two independent pack of the modulated signals for the training and testing phases. Each modulation type has 3600 realizations at different values of SNR from -5 dB to 30 dB (100 realizations in each SNR). Hence, for 7 various modulations it would be 25200 realizations each contains maximum 10 symbols. Besides, for testing phase, SNR values of -10 dB to -6 dB would be added to the mentioned SNRs.

After assigning the testing data sets to the considered structures including the OAO multiclass approach and the developed hierarchical classifier, the average precisions of these two structures have been calculated and represented in Fig. 4. In addition, the average percentages of the correct modulation identification related these two structures can be seen and compared in Table 2. It is worth mentioned that the data packs of the training and testing phases have been generated independently. Also, in order to consider the worst case, each modulated signal has been assumed to contain at least one bit transition as the only intended condition.

Table 2. Overall accuracy rates for different SNR values

Classifier	SNR(dB)				
	5	0	-5	-7	-10
Hierarchical structure	100	100	100	99.8	98.15
OAO Approach	100	100	100	99.75	97.85

Both diagrams and accuracy rates represented in Fig. 4 and Table 2 shows the perfect identification of the considered digital modulation schemes at SNR=-5 dB and a correct percentage of 98.15% at SNR=-10 dB. The obtained results demonstrate that the proposed algorithm outperforms the previous AMR schemes. Meanwhile, it should be noticed that comparing of AMR algorithms are difficult due to their diverse assumptions. However, among the similar existing works which have been investigated in low SNRs [9], [12] and [23-25], the developed algorithm in this paper has considerably high accuracy.

V. CONCLUSION

This paper has proposed a number of robust features for identification of digital modulation schemes. The considered signals include: BASK, BFSK, BPSK, 4-ASK, 4-FSK, QPSK, and 16-QAM. The capability of the introduced features was separately shown in the diagrams representing the variation of the assumed feature against channel noise for different SNRs. The simulation results for a number of random signals demonstrated that with using of the proposed feature set, the complete separation of the supposed digital modulation types is possible in the negative SNR values. After analyzing the introduced features, an AMR algorithm was implemented based on the pattern recognition approach and used these features in the feature extraction block. Furthermore, the SVM classifier has been applied to the classification block and a multiclass structure was developed based on the binary SVMs by using the appropriate features in the each SVM. Finally, the results of the proposed structure were compared to the OAO multiclass approach and the similar results demonstrated that we are able to implement the classification structure with the considerably less number of the binary SVMs. The experimental results demonstrate the outstanding performance of the proposed algorithm developed based on the novel set of features and it outperforms all developed AMR schemes.

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