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Automatic Modulation Recognition in Cognitive Radio Receivers using Multi-Order Cumulants and Decision Trees

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Abstract*: *Design of intelligent receiver is a major footstep in the implementation of Cognitive Radio (CR). Automatic Modulation Recognition (AMR) of the received signal decides the performance of the intelligent receiver. This paper proposes new classification algorithms for AMR using supervised Decision Tree (DT). DT Classifiers (DTC's) are non-parametric classifiers which provide high speed and low complex solutions in classification. Fine Tree (FT), Medium Tree (MT) and Coarse Tree (CT) classifiers are implemented in this paper which is trained with multi-order cumulants to achieve optimum classification accuracy. Performance of DTC's is compared with other classifiers stated in literature to prove their superiority in modulation classification.

Index Terms*: *Modulation Classification, Cognitive Radio, Moments, Cumulants, Binary Trees

I. INTRODUCTION

Adaptive modulation and dynamic carrier selection are playing a major role in data security for military, commercial and CR applications. Quality of Services can be provided by altering the modulation technique dynamically based on the channel characteristics. These techniques involve additional complex operations like spectrum sensing and AMR at transmitter and receiver ends which results in existing traditional receivers are inefficient. Intelligent receivers capable of extracting the modulation information blindly may improve transmission efficiency through reductions in overhead or supplementary information on the modulation type. The functional diagram of an intelligent receiver is shown in Fig. 1.

Modulation classifiers are broadly categorized into maximum likelihood and pattern recognition or feature based classifiers [1]. Probability Density Function (PDF) of the received signal waveform is used for classification in Maximum Likelihood (ML) approaches [2], [3]. Pattern Recognition (PR) approach involves extraction of statistical features, training the classifier and finally testing. The ML classifiers are more accurate than PR classifiers, but they require past knowledge of signal waveform characteristics which is impractical. The PR classifiers are less complex in design and these are signal independent. PR classifiers have poor performance under noisy conditions if proper signal features are not provided for training [4], [5].

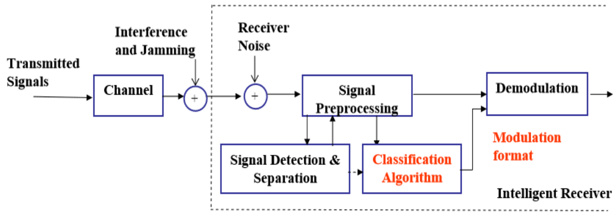

Fig. 1 Block diagram of Intelligent Receiver

To identify the specific modulation, Average and Generalized Likelihood Ratio Tests (ALRT & GLRT) compare received signal likelihood functions with various available modulation functions [6], [7]. Higher order Statics (HoS) or cumulants are used as features for PR classifiers [8], [9]. Cumulants are the best features and the classification accuracy is more even under fading conditions [10]- [12]. Recently hybrid classification approaches are combined cumulants and some other pattern recognition approaches like Back Propagation Neural Network (BPNN), Genetic Programming and KNN (GP-KNN) gives better classification accuracy than Kolmogorov Smirnov (KS) and HoS approaches [13]-[17]. In the last five decades, DT is used in various classification and regression applications [18]. Recently DTC's deals with many data mining, statistics, classification and prediction problems [19].

This paper presents a new automatic recognition approach DTC's for MPSK (M=2, 4 & 8), 4QAM, 16QAM and 64QAM signals through multi-order cumulants. The motivation behind to choose these particular classes is that most of the practical applications involves either MPSK or QAM modulation techniques. In literature, most of the researchers consider MASK, MFSK and limited MPSK and QAM signals for classification. For MASK and MFSK modulation classes, the proposed technique gives optimal classification accuracy similar to existing approaches in literature. So in this paper those modulation classes are excluded for simulation. Simulation results shown, even with more classes of modulation signals, the proposed approaches achieve more accuracy than existing approaches.

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The rest of this paper is organized as follow. Section II describes system model and multi-order features for modulation recognition.

Detailed description of proposed DTC's is presented in Section III. Classification accuracy of DTC's are analyzed through simulation results in Section IV and Section V concludes the work.

II. SYSTEM MODEL

The intelligent receiver system shown in Fig. 1 receives the noisy transmitted signal x(n), and it is given by

$$r(n) = x(n) + a(n) \tag{1}$$

where a(n) is the AWGN noise added in the channel and r(n) is the received signal. In digital data transmission the transmitted signal x(n) is given by [20]

$$x(n) = Ae^{i(2\pi nT f_0 + \theta_n)} \sum_{k=-\infty}^{\infty} x(k)c(n - k + \epsilon)T) \tag{2}$$

Here A is the amplitude, T is symbol time, θ_n is phase jitter, x(k) is input data stream, c(.) is channel effect and ϵ is time shifts due to channel.

To recognize the exact modulation class of received signal statistical features are extracted. Higher order statistical features or cumulants are derived from moments.

The moments are depends on the order of the statistical features and these are given by

$$M_{rs} = E[r(n)^{r-s} r^*(n)^s] \tag{3}$$

Second order cumulants C_{20} and C_{21} are

$$C_{20} = E[r^2(n)] \tag{4}$$

$$C_{21} = E[|r(n)|^2] \tag{5}$$

Fourth order cumulants C_{40}, $C_{41}$and $C_{42}$are

$$C_{40} = M_{40} - 3{M_{20}}^2 \tag{6}$$

$$C_{41} = M_{40} - 3M_{20}M_{21} \tag{7}$$

$$C_{42} = M_{42} - 2M_{21} - |M_{21}|^2 \tag{8}$$

Sixth order cumulants C_{60}, C_{61}, C_{62} and C_{63} are

$$C_{60} = M_{60} + 30{M_{20}}^3 - 15M_{20}M_{40} \tag{9}$$

$$C_{61} = M_{61} + 30M_{20}^2 M_{21} - 10M_{20}M_{41} \tag{10}$$

$$C_{62} = M_{62} - 6M_{20}M_{42} + 24{M_{21}}^2 M_{22} - 8M_{21}M_{41} + 6{M_{20}}^2 M_{22} - M_{22}M_{40} \tag{11}$$

$$C_{63} = M_{63} + 18M_{20}M_{21}M_{22} + 12{M_{21}}^3 - 9M_{21}M_{42} - 3M_{20}M_{43} - 3M_{22}M_{41} \tag{12}$$

Eight order cumulants C_{80} and C_{84} are

$$C_{80} = M_{80} - 630{M_{20}}^4 + 420M_{40}{M_{20}}^2 - 28M_{60}M_{20} - 35{M_{40}}^2 \tag{13}$$

$$C_{84} = M_{84} - 16C_{63}C_{21} + |C_{40}|^2 - 18{C_{42}}^2 - 72C_{42}{C_{21}}^2 - 24{C_{21}}^4 \tag{14}$$

These multi-order cumulants are useful for training the network and testing the received signal. For modulation identification of noisy received signal all multi-order cumulants are calculated then pass these features through trained network for modulation identification.

III. PROPOSED APPROACH

DT classifiers are non parametric supervised learning classifiers. DTC's are simple to understand and fast in classification or prediction. The complexity of these classifiers is less so that they require less memory. The accuracy of DTC's in classification is low under noisy conditions when insufficient features are used for training. Increase in depth of the tree leads to improve in the classification performance. DT classifiers are binary classifiers i.e. any node having two child nodes except leaf nodes. To predict the accurate modulation format, the decision starts from root to leaf node.

Based on the depth (number of leaves) of the tree, DTC's are sub categorized into Fine Tree Classifier (FTC), Medium Tree Classifier (MTC) and Coarse Tree Classifier (CTC). The numbers of leaves in FTC are more, results classification accuracy is high. FTC is suitable for large class dataset. A CTC have minimum number of leaves, so that it provides minimum accuracy among all DTC's. CTC is more robust and easy to interpret for small class problems. A MTC have moderate number of leaves and it provides more accuracy than CTC. In DTC's accuracy of a node depends on Gini's Diversity Index (GDI) and cross entropy. To split the nodes twoing rule is used and by maximizing it, node accuracy will improve.

The detailed DT classifiers algorithm is summarized as follows.

Algorithm

Classifier:

Input: Set of Modulated Signals

Output: Specific Modulation Class

Phase 1: Training

Begin

Step 1: Define set of SNR values

Step 2: Define set of Modulation Classes

Step 3: Generate 'M' signal copies of each modulated class with each and every SNR

Step 4: Extract higher order Moments and Cumulants for all signal copies

Step 5: Identify the best features for Training and discard the remaining features

Step 6: Train the classifier with all SNR signal sets

End

Phase 2: Classification/ Testing

Begin

Step 1: Received signal preprocessing

Step 2: Extract the best features of received signal

Step 3: Apply extracted features to classifier for modulation recognition

Step 4: Calculate the modulation accuracy and misclassification rate

end

The DT classifier block diagram is shown in Fig. 2. It involves training and testing phases. While training, set of reference signals are considered for feature extraction. In this paper , multi-order cumulants is considered as features.

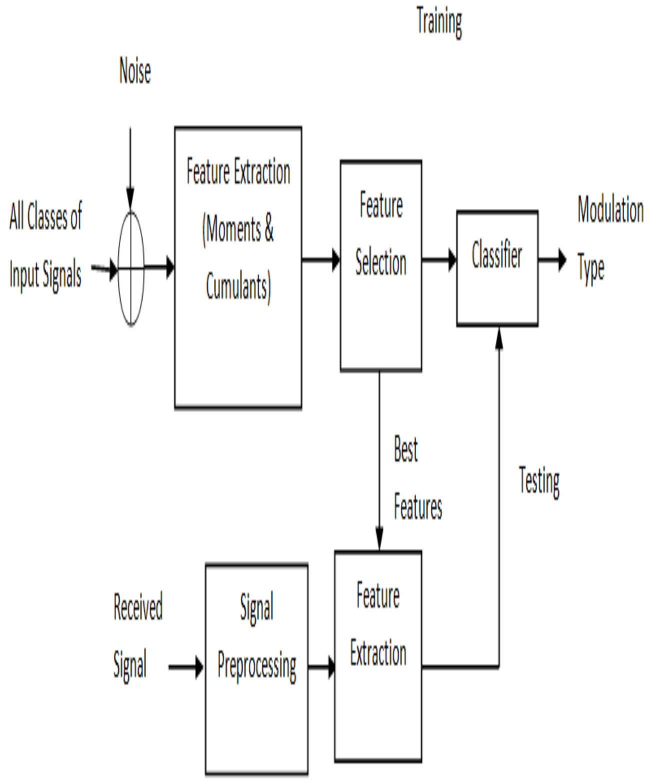
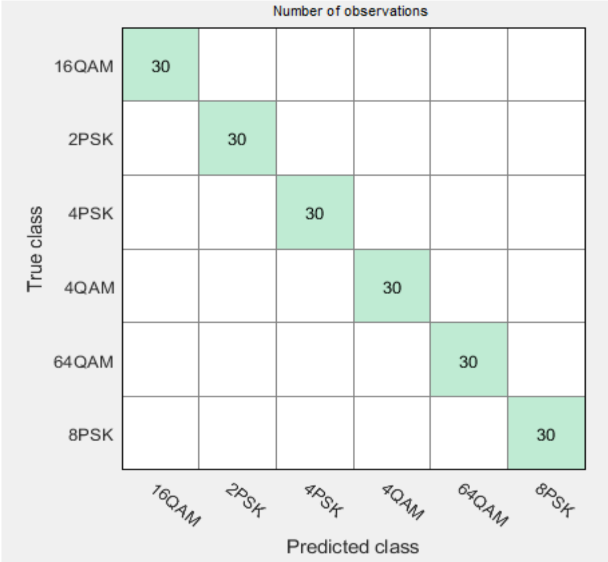


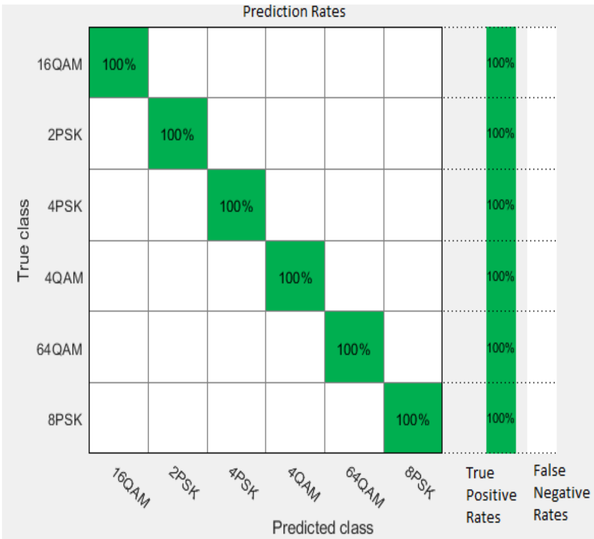
Fig. 2 Decision Tree Classifier Model

IV. SIMULATION RESULTS

M-ary PSK (with M=2, 4 and 8), 4QAM, 16QAM and 64QAM signals are considered for the simulation to verify the superiority of DTC's over existing approaches. To recognize exact modulation, Second, Fourth, Sixth and Eight order moments and cumulants are extracted for all classes of modulated signals under different noisy conditions (AWGN Channel with SNR= 0, 5, 10, 15 and 20 dB's). From the experimental tests, it is found that cumulants are enough for training to achieve optimal classification accuracy, so moments are excluded in training phase to reduce the training time.



(a) Number of Observations

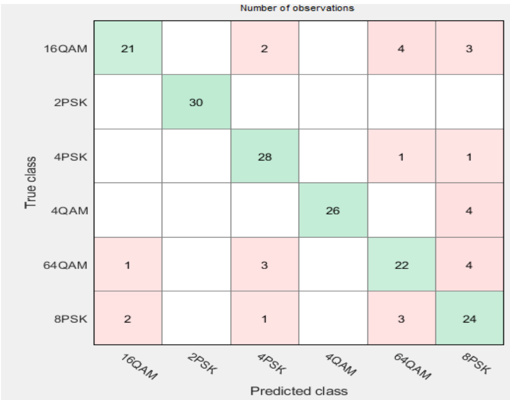


(b) Prediction accuracies

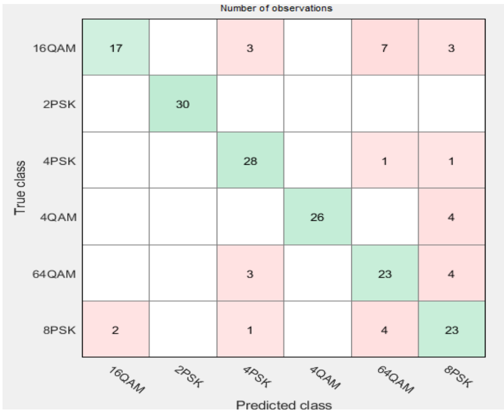
Fig. 3 Confusion Matrices of FN at SNR 20 dB

For better training, every modulated signal is generated 300 times for each SNR value, so that the total feature set size becomes 3600*11. Among these futures, 90% of the features are considered for training and remaining 10% features are used for testing. M-ary PSK, 4QAM, 16 QAM and 64 QAM signals are considered for comparison because most of the existing approaches have a great reduction in accuracy at lower SNR's. For testing, a 30*11 feature set is considered for each modulation technique.

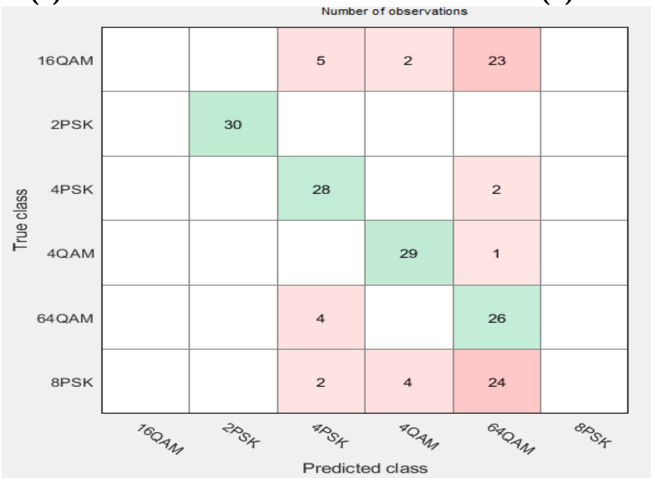
The confusion matrices of proposed FT in terms of observations and prediction rates at 20 dB SNR are shown in Fig. 3, and it's clear that for each modulation among 30 instances FT predicted 30 times accurately. Therefore, the true positive rate of each modulation is 100%. Fig. 4 shows the confusion matrices of FT, MT, and CT at SNR 0 dB. The accurate modulation prediction rate of FT is better than MT and CT for every modulation class even at lower SNR values.



(a) FT



(b) MT



(c) CT

Fig. 4 Confusion matrices of DTC's at SNR 0 dB

Table 1 The Performance Measure of Fine Tree

SNR (dB)	True Class	Predicted Class						Overall % of Accuracy
		BPSK	QPSK	8PSK	4QAM	16QAM	64QAM	
0	BPSK	100						83.9
	QPSK		93	3			3	
	8PSK		3	80		7	10	
	4QAM			13	87			
	16QAM		7	10		70	13	
	64QAM		10	13		3	73	
5	BPSK	100						88.9
	QPSK		100					
	8PSK			97			3	
	4QAM				100			
	16QAM			20		67	13	

	64QAM	7		3		20	70	
10	BPSK	100						95.6
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM			7		86	7	
	64QAM					13	87	
15	BPSK	100						98.9
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM			3		97		
	64QAM					3	97	
20	BPSK	100						100
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM					100		
	64QAM						100	

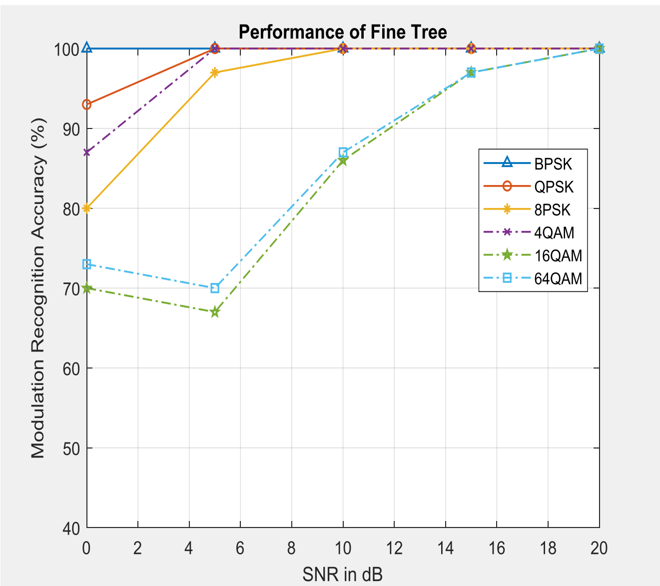


Fig. 5 Recognition Accuracy of Fine Tree

The classification performance of Fine Tree, Medium Tree, and Coarse Tree are shown in Table 1, Table 2 and Table 3 respectively. From Tables 1 & Table 2, it is observed that FT and MT almost have same performance apart from lower SNR values. From Table 3, CT has more confusion in the classification of 8 PSK, 16 QAM, and 64 QAM signals so that the performance never reaches to 100%. At SNR values of 10 dB and 5 dB, the accuracy of FT is similar to MT, but there is a variation in the classification in terms of prediction.

The recognition accuracy of FT for different modulation techniques is shown in Fig. 5. The FT provides optimal accuracy for MPSK and 4QAM signals even for lower SNR values, but the performance is degraded for 16QAM and 64QAM signals at SNR 5dB and 0dB. Similarly, the performance of MT for different modulation classes is shown in Fig. 6. The performance of MT is almost similar to FT for MPSK and 4QAM signals. The accuracy is slightly varying for 16QAM and 64QAM signals.

Table 2 The Performance Measure of Medium Tree

SNR (dB)	True Class	Predicted Class						Overall % of Accuracy
		BPSK	QPSK	8PSK	4QAM	16QAM	64QAM	
0	BPSK	100						81.7
	QPSK		93	4			3	
	8PSK		3	77		7	13	
	4QAM			13	87			
	16QAM		10	10		57	23	
	64QAM		10	13			77	
5	BPSK	100						88.9
	QPSK		100					
	8PSK			97			3	
	4QAM				100			
	16QAM			20		67	13	
	64QAM	7		3		20	70	
10	BPSK	100						95.6
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM			7		86	7	
	64QAM					13	87	
15	BPSK	100						98.9
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM			3		97		
	64QAM					3	97	
20	BPSK	100						100
	QPSK		100					

	8PSK			100				
	4QAM				100			
	16QAM					100		
	64QAM						100	

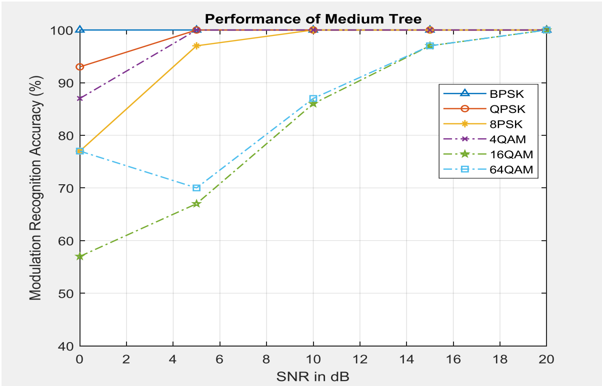


Fig. 6 Recognition Accuracy of Medium Tree

Table 3 The Performance Measure of Coarse Tree

SNR (dB)	True Class	Predicted Class						Overall % of Accuracy
		BPSK	QPSK	8PSK	4QAM	16QAM	64QAM	
0	BPSK	100						62.8
	QPSK		93				7	
	8PSK		7		13		80	
	4QAM				97		3	
	16QAM		17		7		77	
	64QAM		13				87	
5	BPSK	100						78.3
	QPSK		100					
	8PSK			83			17	
	4QAM				100			
	16QAM			37		0	63	
	64QAM		7	7			86	
10	BPSK	100						83.3
	QPSK		100					
	8PSK			100				

	4QAM				100			
	16QAM			7			93	
	64QAM						100	
15	BPSK	100						83.3
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM			3			97	
	64QAM						100	
20	BPSK	100						83.3
	QPSK		100					
	8PSK			100				
	4QAM				100			
	16QAM					100		
	64QAM					100		

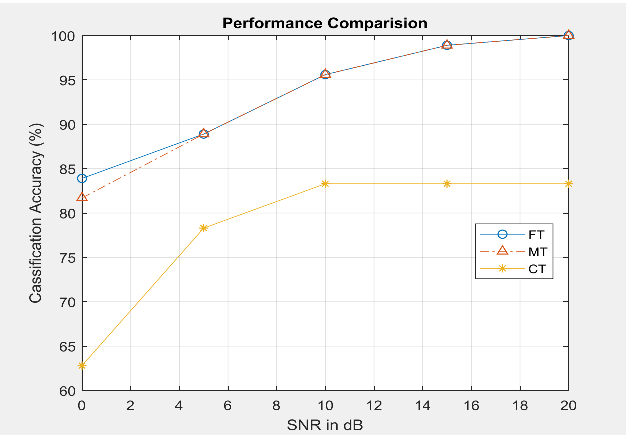


Fig. 7 Classification Accuracy of Decision Trees

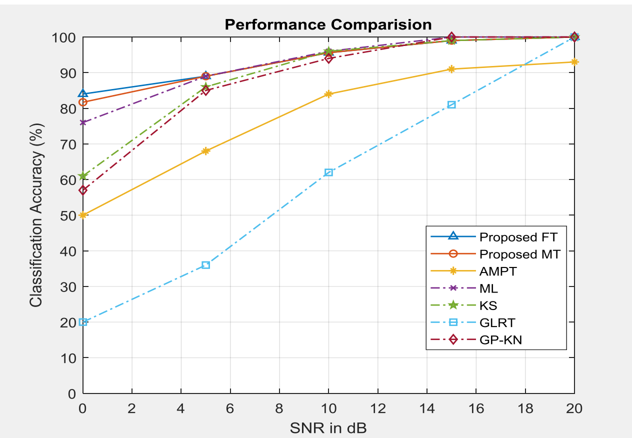


Fig. 8 Performance Comparison of DTC's with Existing Approaches

Fig. 7 represents the performance of fine, medium and coarse trees at different SNR values. Among three FT and MT provides better classification accuracy than CT because it fails to distinguish between 16QAM and 64QAM, this reason CT is not consider for final comparison. The performance comparison of proposed FT and MT with some of the available approaches in the literature is shown in Fig. 8. Most of the existing approaches are consider limited MPSK, MQAM signals along with MASK and MFSK signals. As the number of modulation techniques increases, then the performances of existing approaches are degraded. With all classes of MPSK and QAM signals, the proposed decision trees gave more classification accuracy for lower SNR values too. From these simulation results, it is clear that decision trees can provide optimal classification accuracy in modulation recognition under noisy channels.

V.CONCLUSION

This paper presented decision tree approaches for automatic modulation recognition of digitally modulated signals. Earlier, these decision trees are applied to the various image and statistical data analysis. The limitation of decision trees is accuracy which may vary based on characteristics of the data. The simulation results proved that even under high noisy conditions proposed, fine tree and medium trees give improved classification accuracy than existing approaches. The complexities of the proposed approaches are far lesser than traditional approaches due to their simple approaches in classification. In future, these techniques are also applicable to various signal classifications and communication signals under fading conditions.

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