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Research Article

Efficient and Low Complexity Modulation Classification Algorithm for MIMO Systems

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Abstract: This study develops a feature-based Automatic Modulation Classification (AMC) algorithm for spatially multiplexed Multiple-Input Multiple-Output (MIMO) systems employing two Higher Order Cumulants (HOCs) of the estimated transmit signal streams as discriminating features and a multiclass Support Vector Machine (SVM) as a classification system. The algorithm under study has the capability to recognize a wide range of modulation schemes without any prior information about the channel state. The classification performance of the proposed algorithm was evaluated via extensive simulations under different operating conditions and was also compared with the one obtained with the optimal Hybrid Likelihood Ratio Test (HLRT) approach. The results show that the proposed algorithm is capable of classifying the considered modulation schemes with good classification accuracy and can achieve performance comparable to that of the HLRT approach while having a significantly lower computational complexity.

Keywords: Automatic modulation classification, higher-order cumulants, multiple-input multiple-output, support vector machine

INTRODUCTION

Automatic Modulation Classification (AMC) is a signal processing technique that automatically recognizes the modulation type of a received signal with limited or no prior knowledge about the parameters of the signal (MacKenzie *et al*., 2009). Although AMC was initially proposed and developed for military applications, recent years have witnessed a rapid expansion of its employment to cover many civilian applications. For military purposes, AMC can be used in Electronic Warfare (EW) systems, such as for Electronic Surveillance (ES), threat detection analysis and Electronic Protect (EP). Other applications are for civil purposes such as spectrum management, Software Defined Radio (SDR) and Cognitive Radio (CR) (MacKenzie *et al*., 2009).

Even though intense researches have been carried out in the field of AMC during the last decades, most of them were mainly conducted for Single-Input Single-Output (SISO) systems. Over the years, a large number of algorithms have been proposed in the literature to address the AMC problem for SISO systems. They are typically grouped into two main classes; likelihood-based and feature-based algorithms (Dobre *et al*., 2007). The decision in the former algorithms is made by computing the likelihood function of the detected signal under different hypotheses and comparing the likelihood ratio against a Bayesian-criterion-determined threshold. For the feature-based algorithms, the decision is made by extracting some features and comparing their values with previously observed ones (Dobre *et al*., 2007).

Recently, Multiple-Input Multiple-Output (MIMO) techniques have attracted much attention and gained more popularity. This is because they can enhance the data rate and/or robustness of the wireless links without the need for any increase in transmit signal power or bandwidth. However, the transmission over multiple antennas makes the previous AMC algorithms (i.e., the algorithms proposed for SISO systems) not suitable for MIMO systems and raises the necessity for new AMC algorithms that can operate in such environments (Hassan *et al*., 2012). In practice, the modulation classification for MIMO systems is more challenging than for SISO due to the mutual interference introduced by the MIMO channel. Accordingly, a blind channel equalization technique will be needed in order to perform properly the modulation classification for MIMO systems (Hassan *et al*., 2012).

Up to now, little research has been carried out in the area of AMC for MIMO systems. In Choqueuse *et al*. (2009), two likelihood-based AMC algorithms for spatially multiplexed MIMO systems are proposed. The first approach, referred to as Average Likelihood Ratio Test (ALRT), provides optimal decisions in a Bayesian sense but under the assumption of perfect Channel State Information (CSI). The second one, referred to as

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Hybrid Likelihood Ratio Test (HLRT), is more realistic since the true channel is replaced with its estimate. However, both algorithms have a high computational complexity especially when a high-order modulation scheme and/or a large-number transmit antenna are employed; therefore their practical implementations are greatly limited (Hassan *et al*., 2012).

In Hassan *et al*. (2010, 2012), feature-based AMC algorithms for MIMO systems are proposed by using the multilayer feed-forward Artificial Neural Network (ANN) as a classification system and the M-out-of-N rule as a decision fusion rule. The study of Hassan *et al*. (2010) takes into consideration both space-time coding and spatial multiplexing MIMO systems, but under the assumption of perfect CSI and coding information. However, this assumption is unrealistic since this information is generally unavailable when utilizing AMC algorithms in real wireless communication scenarios. The other study (Hassan *et al*., 2012) addresses the AMC problem for spatially-correlated MIMO systems and it covers cases with and without CSI. However, the applied neural network algorithms suffer from many drawbacks such as complex structure, long training time and slow convergence rate (Islam *et al*., 2014).

In Mŭhlhaus *et al*. (2012, 2013), low complex feature-based AMC algorithms for spatially multiplexed MIMO systems are proposed by using the Euclidean distance as a classification system and a simple weighted sum rule as a feature fusion rule. Cases with and without CSI are covered in these algorithms. While the Mŭhlhaus *et al*. (2012) uses only the fourth-order cumulant of the estimated transmit signal stream as a discriminating feature, the authors have extended their study in Mŭhlhaus *et al*. (2013) to investigate the performance when employing various higher-order cumulants as features; such as sixth or eighth-order cumulants. However, these algorithms cover only a limited number of modulation schemes. Furthermore, the suggested fusion scheme will be inefficient if a wider set of modulation schemes is considered.

The most recent literature (Chikh *et al*., 2014) addresses the AMC problem for MIMO relay systems under the assumption of perfect CSI for all wireless links. This study shows the performance improvement when performing the AMC based on cooperative schemes.

As seen from the literature, the feature-based algorithms were found to be the most widely used methods to addresses the AMC problem for MIMO systems. This is due to their low computational complexity and acceptable classification accuracy in comparison with the likelihood-based algorithms. However, most of these feature-based algorithms usually rely on perfect knowledge of CSI (Hassan *et al*., 2010), are computationally intensive (Hassan *et al*., 2012), or can classify only a limited number of modulation schemes (Mŭhlhaus *et al*., 2012).

In this study, an efficient and low complexity feature-based AMC algorithm for spatially multiplexed MIMO systems is presented. The proposed algorithm has the capability to recognize a wide range of modulation schemes without any prior information about the channel state. The performance of the proposed algorithm is evaluated via simulations and compared with that of the optimal HLRT approach (i.e., the optimal approach with blind channel estimation) provided in Choqueuse *et al*. (2009).

METHODOLOGY

Signal model: A spatial multiplexing MIMO system with M_T transmit antennas and $M_R \geq M_T$ receive antennas is considered in this study. Under the assumption that the channel is time invariant and frequency flat, the received symbol vector at time instant k can be expressed as:

$$\mathbf{r}\,(k) = \mathbf{Hs}\,(k) + \mathbf{n}\,(k) \tag{1}$$

where,

- k : The reception time instant of the symbol vectors
- $\mathbf{r}\,(k)$: The $M_R \times 1$ received symbol vector under the assumption of perfect carrier frequency and phase recovery
- $\mathbf{s}\,(k)$: The $M_T \times 1$ transmitted symbol vector whose elements are assumed to be independent and identically distributed (i.i.d) and belong to the same modulation scheme
- $\mathbf{n}\,(k)$: The $M_R \times 1$ additive background noise vector which corresponds to the zero-mean spatially-white circularly-symmetric complex Gaussian noise with variances σ_n^2
- $\mathbf{H}$: The $M_R \times M_T$ complex channel matrix

A Rayleigh fading channel is considered in this study; thus all complex entries of $\mathbf{H}$ are assumed to follow a zero-mean circularly-symmetric complex Gaussian distribution with unit variance.

Without loss of generality, the transmitted signals are assumed to have unity average power; hence the average SNR can be expressed as SNR = 10 log (M_T/σ^2_n) (Choqueuse *et al*., 2009). Moreover, we assume that the noise variance σ_n^2 and the number of transmit antennas M_T are known or correctly estimated at the receiver side.

Proposed classification algorithm: The proposed algorithm has four main stages as shown in Fig. 1.

In the first stage, blind channel equalization (i.e., blind channel estimation and compensation) is performed to recover the M_T transmit signal streams from the received mixtures. Then, in the second stage, a

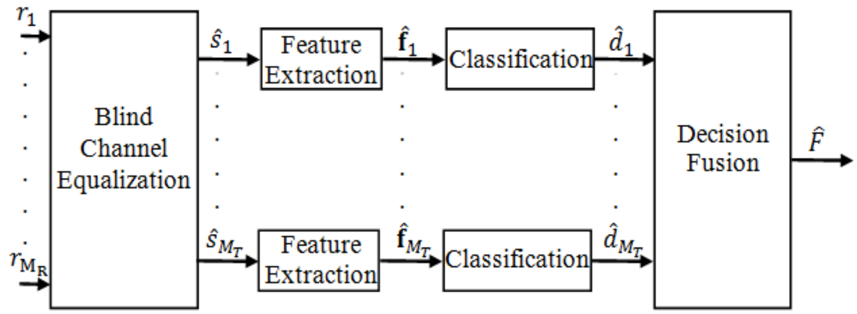

Fig. 1: A block diagram of the proposed AMC algorithm

set of robust and discriminative features for modulation classification is extracted for each of the M_T streams. Next, based on the extracted features, a properly trained classifier is utilized in the third stage to estimate the modulation type for each stream. Finally, the estimated decisions for the streams are fused to form the final classification decision $\hat{F}$. All the stages are discussed below in more detail.

Blind channel equalization: Since the components of the received signal vector are linear mixtures of the components of the transmitted signal vector plus white noise, a blind channel equalization technique is required to extract the transmitted symbol streams from their noisy linear combinations.

Independent Component Analysis (ICA) (Choi *et al*., 2005), which is used in this study, is one of the most common and well-established techniques to solve this problem.

However, the ICA technique can blindly recover the transmit signal streams as far as the following assumptions are met: the transmitted streams are mutually statistically independent; at most one of the streams may have a Gaussian distribution; the number of streams (i.e., number of transmit antennas) is less than or equal to the number of mixtures (i.e., number of receive antennas) (Choi *et al*., 2005). Obviously, the system proposed in this study fulfills all these requirements.

Several algorithms based on different criteria have been proposed so far to perform the ICA. Due to its high convergence speed and acceptable separation accuracy in a wide variety of applications (Agirman-Tosun *et al*., 2011), the Joint Approximate Diagonalization of Eigen-matrices (JADE) algorithm (Cardoso, 1999) is used in this study to perform ICA.

In practice, JADE algorithm permits us to estimate the channel matrix up to a phase and a permutation ambiguity. In other words, under the assumption of perfect separation, the true channel matrix can be written as (Choqueuse *et al*., 2009):

$$\mathbf{H} = \hat{\mathbf{H}}\mathbf{D}\mathbf{P} \tag{2}$$

where,

$\hat{\mathbf{H}}$: The channel matrix estimated by JADE

$\mathbf{D}$: A diagonal complex-valued matrix containing the phase ambiguities

$\mathbf{P}$: A permutation matrix

Accordingly, the transmitted symbol vector at time instant k can be expressed as (Choqueuse *et al*., 2009):

$$\hat{\mathbf{s}}\,(k) = \hat{\mathbf{H}}^{-1}\mathbf{r}\,(k) = \mathbf{DPs}\,(k) + \hat{\mathbf{H}}^{-1}\mathbf{n}\,(k) = \mathbf{DPs}\,(k) + \hat{\mathbf{n}}\,(k) \tag{3}$$

where,

$\hat{\mathbf{n}}\,(k)$: The filtered noise vector at the time instant k

Note that JADE algorithm is able to recover the transmitted symbol streams up to a phase and a permutation ambiguity. It is clear that permutation matrix has no effect on the overall AMC performance since the ordering is not that important for the AMC algorithms (Choqueuse *et al*., 2009). However, the phase ambiguity inherited from the JADE should be taken into consideration in the next stage when choosing the features; otherwise a phase correction stage is needed.

Feature extraction: The feature extraction is performed in the second stage of the proposed algorithm for each of the M_T transmit signal streams estimated in the previous stage-as depicted in Fig. 1, where a set of robust and discriminative features for modulation classification is considered.

Many feature types have been proposed so far in the context of modulation classification. In practice, it is very important to have a proper selection of the features as it highly affects the computational efficiency and classification accuracy of the AMC algorithm.

Recent studies conducted in the field of modulation classification (Hazza *et al*., 2013; Mửhlhaus *et al.*, 2013) have shown that Higher Order Cumulants (HOCs) of the received signal can be regarded as one of the best candidates to classify the modulation type of a signal in SISO (Hazza *et al*., 2013) and also MIMO

Table 1: Theoretical values of the features for the considered modulated signals

	Scheme					
Cumulant	BPSK	4-PSK	8-PSK	16-PSK	16-QAM	64-QAM
$\tilde{C}_{42}$	-2	-1	-1	-1	-0.680	-0.619
$\lvert\tilde{C}_{80}\rvert$	272	34	1	0	13.988	11.502

systems (Mŭhlhaus *et al*., 2013). This is due to their robustness to constellation rotation, resistance to additive Gaussian noise and easiness to implementation (Hazza *et al*., 2013; Mŭhlhaus *et al*., 2013).

However, in this study, only two HOCs are used as discriminating features for modulation classification; they are the normalized fourth-order cumulant ($\tilde{C}_{42}$) and the magnitude of the normalized eighth-order cumulant ($|\tilde{C}_{80}|$).

These features ($\tilde{C}_{42}$,$|\tilde{C}_{80}|$) are chosen since they are robust to phase rotation (Swami and Sadler, 2000; Mŭhlhaus *et al*., 2013) which in our study corresponds to the phase ambiguity introduced by the JADE algorithm. Additionally, they are capable to reliably characterize the modulated signals considered in this study (Ghosh *et al*., 2013; Mŭhlhaus *et al*., 2013).

For a random variable x, associated with a stationary random process for the data sequence x (k), the $\tilde{C}_{42}$ and $|\tilde{C}_{80}|$ can be respectively defined as (Xi and Wu, 2006; Ghauri *et al*., 2013; Ghosh *et al*., 2013):

$$\tilde{C}_{42} = \frac{E(|x|^4) - |E(x^2)|^2 - 2E^2(|x|^2)}{E^2(|x|^2)} \tag{4}$$

$$|\tilde{C}_{80}| = \left|\frac{E(x^8) - 35E^2(x^4) - 28E(x^6)E(x^2) + 420E(x^4)E^2(x^2) - 630E^4(x^2)}{E^4(|x|^2)}\right| \tag{5}$$

where,
$E(\cdot)$: The statistical expectation operator

Note, we choose to use the magnitude of the normalized eighth-order cumulant in order to make the feature robust to phase offsets (Mŭhlhaus *et al.*, 2013).

The theoretical values of $\tilde{C}_{42}$ and $|\tilde{C}_{80}|$ for the modulated signals of interest are given in Table 1. These values are computed by (4), (5) over the ideal (noise-free) channels.

SVM based classification: Based on the features extracted in the previous stage, the classification is carried out in the third stage of the proposed algorithm to identify the modulation type for each estimated transmit signal stream-as shown in Fig. 1.

Recent AMC literature (Hazza *et al*., 2013) has demonstrated that Support Vector Machine (SVM) approaches outperform traditional statistical and neural approaches in classifying the modulated signals. This is due to their significant characteristics such as good generalization capability and powerful learning ability (Hazza *et al*., 2013). Thus, an SVM-based classifier is used in this study.

Although SVM was originally proposed for binary classification problems (two-class classifier), its employment was later extended to handle multiclass classification problems; where the *M*-class classification problem is treated as *M* two-class classification problems (Lorena *et al*., 2008). Due to its low computational complexity and good classification accuracy (Arun Kumar and Gopal, 2011), the one-against-all scheme is used in this study used to extend SVM to multiclass classification case.

The SVMs perform the classification by mapping the input data into a high dimensional feature space via kernel functions and constructing an Optimal Separating Hyper-plane (OSH) in this space with a maximum margin (Jiang and Chen, 2014). Moreover, the SVMs employ a regularization parameter C (also referred to as a penalty factor) to control the trade-off between the separation margin and misclassification error (Jiang and Chen, 2014).

Many kernel functions have been proposed so far, with the most commonly used ones are of the linear, radial basis (Gaussian) and polynomial functions. In this study, the kernel function was studied empirically and the best classification results were found using the Radial Basis Function (RBF) which is given by the following formula (Min and Lee, 2005):

$$K\left(\mathbf{f}_i, \mathbf{f}_j\right) = \exp\left(-\frac{\|\mathbf{f}_i - \mathbf{f}_j\|^2}{2\,\sigma^2}\right) \tag{6}$$

where,
$K\left(\mathbf{f}_i, \mathbf{f}_j\right)$: The kernel function
$\mathbf{f}_i, \mathbf{f}_j$: The feature vectors
σ : A kernel parameter

The kernel parameter σ and the SVM regularization parameter C ought to be carefully selected so that the RBF-SVM can achieve accurate classification results (Jiang and Chen, 2014).

Decision fusion: After classification of the modulation scheme for each estimated transmit signal stream, the decisions are fed to the Fusion Center (FC); where they are fused to generate the final classification decision-as depicted in Fig. 1.

The decision fusion rule at the FC can typically be OR, AND, or Majority rule, which is often generalized as the M-out-of-N rule (Hassan *et al*., 2012).

Due to its simplicity and reliability, the majority decision fusion rule (M-out-of-N rule, where $M = N/2$) is employed in this study to obtain the final classification decision $\hat{F}$.

Complexity analysis: The complexity order of the algorithm ($\mathcal{O}$) can be expressed as the sum of the complexity orders of the blind channel equalization ($\mathcal{O}_{\text{JADE}}$), the feature extraction ($\mathcal{O}_{\text{HOC}}$), the classification ($\mathcal{O}_{\text{SVM}}$) and the decision fusion ($\mathcal{O}_{\text{DF}}$) stage, that is:

$$\mathcal{O} = \mathcal{O}_{\text{JADE}} + \mathcal{O}_{\text{HOC}} + \mathcal{O}_{\text{SVM}} + \mathcal{O}_{\text{DF}} \quad (7)$$

where, the complexity order of each stage is approximated by $\mathcal{O}_{\text{JADE}} \cong \mathcal{O}\ (M_R^2 + M_T^4 N + M_T^5)$ (N is the observation interval length) (Gao *et al*., 2009); $\mathcal{O}_{\text{HOC}} \cong \mathcal{O}\ (M_T N_{HOC} N)$ (N_{HOC} is the number of HOCs features) (Kharbech *et al*., 2014); $\mathcal{O}_{\text{SVM}} \cong \mathcal{O}\ (M_T d N_S m^2)$ (d is the number of kernel operations, N_S is the number of support vectors, m is the number of modulation schemes) (Ayyildiz and Conrad, 2013); and $\mathcal{O}_{\text{DF}} \cong \mathcal{O}\ (M_T)$. It should be noted here that the naturals M_R, M_T, N_{HOC}, d, N_S and m can be neglected when compared to the observation interval length N.

RESULTS AND DISCUSSION

Extensive Monte-Carlo (MC) simulations were carried out in MATLAB to evaluate the performance of the proposed algorithm and also compare it with an optimal approach introduced in an earlier study.

MIMO Signals with the BPSK, QPSK, 8PSK, 16PSK, 16-QAM and 64-QAM modulations were considered in this study as they belong to the most widely used modulations that can be found in the radio spectrum.

First, two hundred signal realizations were generated for each considered modulation scheme and SNR value. Each realization consisted of $4096 \times M_T$ symbols considering the following configuration $M_T = 2$, $M_R = 4$. For each processed signal, the features were calculated according to Eq. (4) and (5) to form the feature set. These realizations were employed only for SVM training.

In this study, the multi-class SVM was implemented using LIBSVM package (Version 3.18) (Chang and Lin, 2011). The SVM regularization parameter C and the RBF parameter σ were chosen based on a trial-and-error method so that the SVM could achieve accurate classification results.

The classification performance of the proposed algorithm was presented in the form of probability of correct classification (P_{cc}) averaged over all the considered modulation schemes and over a large number of trials.

Unless otherwise noted, one thousand MC trials were performed for each modulation scheme and SNR value in the range -10 to 15 dB. For each MC trial, N = 4096 i.i.d symbols per transmit antenna was considered as an observation interval and $M_T = 2$, M_R = 4 as MIMO antenna configuration, unless otherwise noted.

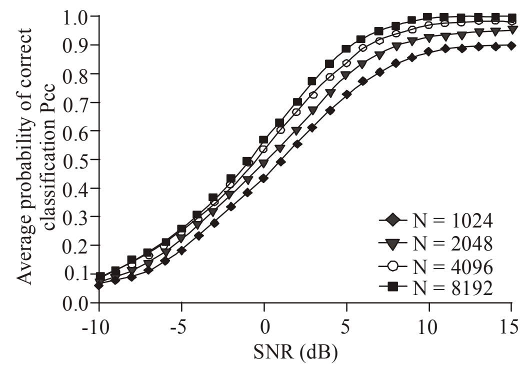

Fig. 2: Average probability of correct classification versus SNR for different observation interval lengths

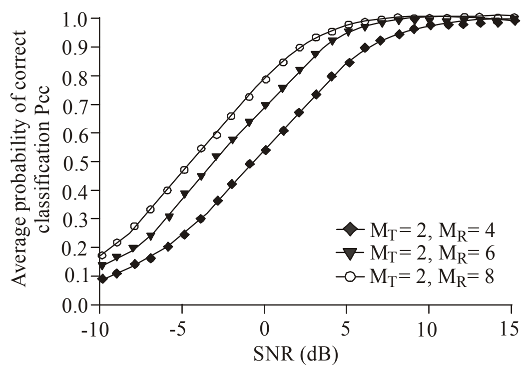

Fig. 3: Average probability of correct classification versus SNR for different MIMO antenna configurations

Figure 2 shows the effect of the observation interval length N on the average P_{cc} over a wide range of SNR (-10 to 15 dB) where M_T is set to 2 and M_R set to 4. Note that, as expected, the algorithm performance improves as N increases. The reason is that, as the observation interval length (i.e., number of the considered symbols) increases, the reliability and accuracy of the extracted statistical features will also increase, leading to a remarkable improvement in the algorithm overall performance. For instance, at SNR equal to 10 dB, the average P_{cc} = 88, 93 and 98% for N = 1024, 2048 and 4096, respectively, whereas it is close to 100% for N = 8192.

Figure 3 shows the average P_{cc} achieved with the proposed algorithm over a wide range of SNR (-10 to 15 dB) for different MIMO antenna configurations where M_T is set to 2 and M_R to 4, 6 and 8, respectively. As illustrated in the figure, the performance improves as the difference $(M_R - M_T)$ increases. The reason for this improvement is that, as the difference $(M_R - M_T)$ increases, the diversity gain will also increases, leading to a reduction in the symbol error probability and accordingly an enhancement in the algorithm overall

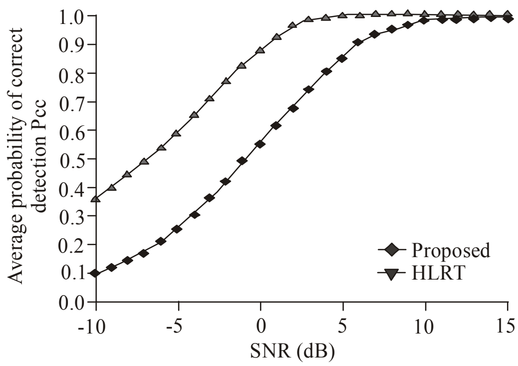

Fig. 4: Performance comparison of the proposed approach with that of the HLRT approach when M_T = 2 antennas, M_R = 4 antennas

performance (Hassan *et al*., 2012). Note that for the all considered antenna configurations, the average P_{cc} achieved with the proposed algorithm is close to 90% when SNR is not lower than 6 dB.

Figure 4 compares the performance of the proposed algorithm with that of the HLRT approach presented in Choqueuse *et al*. (2009) where 300 trials are performed for each modulation scheme. As expected, the HLRT approach achieves better performance than the proposed one since it relies on a likelihood ratio test to find the classification decision. Note that the performance difference is not that significant. For instance, at P_{cc} equal to 90%, the performance difference is only about 5 dB. However, the overall complexity order for the proposed algorithm can be approximated by $\mathcal{O}\ (N \times M_T)$ which is significantly lower than $\mathcal{O}\ (N \times M_u^{M_T})$ for the HLRT approach; where M_u is the number of possible states for the considered constellations (e.g., $M_u = 16$ in the case of 16-QAM) (Agirman-Tosun *et al*., 2011). Since both the HLRT and the proposed approaches employ JADE algorithm, the computational cost that comes as a result of the blind channel estimation stage is not considered when comparing the computational complexity.

CONCLUSION

In this study, an efficient and low complexity feature-based AMC algorithm for spatially multiplexed MIMO systems is presented. The proposed algorithm is able to recognize a wide range of modulation schemes without any prior knowledge about the channel state.

Simulations show that the proposed algorithm works well under different operating conditions over an acceptable range of SNR. Furthermore, the simulations indicate that our algorithm has a comparable performance to that of the HLRT approach while having a significantly lower computational complexity. Accordingly, the proposed approach is more suitable for the practical and real-time applications.

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