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Robust and Reliable Modulation Classification for MIMO Systems

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Abstract: This paper develops a feature-based Automatic Modulation Classification (AMC) algorithm for spatially multiplexed Multiple-Input Multiple-Output (MIMO) systems. The proposed algorithm employs 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. A multi-classifier classification system is introduced to improve the robustness of the decision made by the classifier at each estimated transmit signal stream. Furthermore, an optimal decision fusion scheme using a Maximum-Likelihood (ML) criterion is also introduced to improve the accuracy and reliability of the final classification decision made in the fusion center. The proposed algorithm shows good performance under different operating conditions, over an acceptable range of SNR, without any prior information about the channel state.

Keywords: Automatic modulation classification, blind channel estimation, decision fusion, higher-order cumulants, multiple-input multiple-output.

1 Introduction

Automatic modulation classification (AMC) is a signal processing technique that automatically identifies the modulation type of the incoming signal with limited or no prior knowledge about the parameters of the signal [1]. It was originally proposed for military applications, but later its employment was extended to cover many civilian applications [2].

Even though intense researches have been conducted in the field of AMC during the last decades, most of them were mainly conducted for Single-Input Single-Output (SISO) systems. Recently, Multiple-Input Multiple-Output (MIMO) techniques have been receiving much attention and widely employed by various wireless systems. This is because they can enhance reliability and/or data rate of communications over the wireless channels [3,4]. However, the transmission over multiple antennas makes the previous AMC algorithms (i.e., the algorithms proposed for SISO systems) invalid for MIMO systems, and raises the necessity for new algorithms that can handle such environments well [5]. In practice, the AMC algorithms for MIMO systems pose a much more challenging tasks compared to that for SISO due to the mutual interference introduced by the MIMO channel [6].

Many algorithms have been developed so far to address AMC problem for MIMO systems. These algorithms are typically categorized into two main classes; likelihood-based (e.g., [5]) and feature-based (e.g., [6] and [7]) algorithms.

Through an exhaustive review of the literature, the feature-based algorithms were found to be the most widely used methods to addresses the AMC problem for spatially multiplexed MIMO systems. This is due to their lower computational complexity and reasonable classification accuracy when compared with the likelihood-based algorithms [6]. However, for the most of these existing feature-based algorithms, the decisions for the estimated transmit signal streams (i.e., the separated data streams at the output of the MIMO equalizer) are usually made and fused without considering the Post-Processing Signal-to-Noise Ratio (PPSNR) at these streams - assuming that all estimated streams have the same PPSNR. In particular, the extracted features, and therefore the decision for each estimated stream are closely dependent on its PPSNR. Therefore, to achieve a more reliable and robust classification result, it is necessary for the classification system and also the fusion scheme to incorporate the SNR conditions at the

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estimated streams when making and fusing the decisions for these streams.

In this paper, a feature-based AMC algorithm for spatially multiplexed MIMO systems is presented. The proposed algorithm considers the SNR conditions at the estimated transmit signal streams when making and fusing the decisions for these streams. For this purpose, a multi-classifier classification system similar to that in [7] is proposed to be utilized at each estimated stream; each sub-classifier is trained to be able to operate under a specific range of SNR. However, instead of estimating the average SNR per receiver antenna as in [7], the PPSNR for each estimated stream is calculated at the output of the MIMO channel equalizer and used to adapt the classification system to the SNR condition of the stream. Thus, more robust and reliable decisions can be made by the classification system. To our best knowledge, this approach has never been used in the context of the feature-based AMC algorithms for MIMO systems. Furthermore, instead of treating all estimated decisions at the Fusion Center (FC) equally, a decision fusion scheme using a Maximum-Likelihood (ML) criterion is proposed to be utilized in the FC in order to reach the final classification decision; the modulation type is thought to be the most probable reason behind the observed decisions under specific PPSNR conditions. Thus, more accurate final classification decisions can be made in the FC. Again, to our best knowledge, no previous work addressed the problem of the decision fusion in the context of AMC for MIMO systems.

The rest of this paper is arranged as follows. Section (2) describes the signal model and related assumptions. Section (3) presents the proposed modulation classification algorithm in details. Section (4) presents the simulation results, and finally Section (5) concludes the whole paper.

In this paper, the bold-face lower-case letters, bold-face upper-case letters and lower-case letters denote vectors, matrices and scalars, respectively. For the inverse, transpose, and conjugate transpose operations we use the respective $(\cdot)^{-1}$, $(\cdot)^{T}$ and $(\cdot)^{H}$.

2 Signal Model

A spatial multiplexing MIMO system equipped with M_T transmit antennas and M_R receive antennas is considered in this study where $M_T \geq M_R$. Assuming a frequency-flat time-invariant channel environment, the received symbol vector at a certain time instant k can be expressed as:

$$\mathbf{r}(k) = \mathbf{H}\mathbf{s}(k) + \mathbf{n}(k) \tag{1}$$

Where $\mathbf{r}(k) \in \mathbb{C}^{M_R \times 1}$ is the received symbol vector at time instant k under the assumption of perfect carrier frequency and phase recovery; $\mathbf{s}(k) \in \mathbb{C}^{M_T \times 1}$ is the transmitted symbol vector at time instant k whose elements are assumed to be independent and identically distributed (i.i.d) belonging to the same modulation scheme; $\mathbf{n}(k) \in \mathbb{C}^{M_R \times 1}$ is the additive background noise vector at time instant k corresponds to the zero-mean spatially-white circularly-symmetric complex Gaussian noise with variances σ_n^2; and $\mathbf{H} \in \mathbb{C}^{M_R \times M_T}$ is the complex MIMO channel matrix whose elements represent the path gain between the transmit and receive antennas.

We consider a Rayleigh fading channel, thus all complex elements of $\mathbf{H}$ are assumed to follow a zero-mean circularly-symmetric complex Gaussian distribution with unit variance.

Without loss of generality, the signal transmitted from each antenna is assumed to have unity average power; hence the average SNR can be expressed as SNR = $10log(M_T/\sigma_n^2)$.

Moreover, the noise variance σ_n^2 and the number of transmit antennas M_T are assumed to be perfectly known or accurately estimated at the receiver side, for instance by means of the covariance matrix of the received samples.

3 Classification Algorithm

The proposed algorithm has four main stages as shown in Fig. (1). Firstly, blind channel equalization (i.e., blind channel estimation and compensation) is performed to estimate the M_T transmitted symbol streams from the received mixtures. Moreover, based on the channel estimates, the computation of the PPSNR for each of the M_T streams is also performed. Then, in the second stage, features for modulation classification are extracted for each of the M_T streams where a set of robust and discriminative features are estimated. Next, based on the extracted features and the PPSNR for each estimated stream, a properly trained classifier is utilized in the third stage to estimate the modulation type at each stream. Finally, based on the estimated decisions and PPSNRs for all streams, an optimal decision fusion scheme is utilized in the fourth stage to find the final classification decision F. All the proposed algorithm stages are discussed below in detail.

3.1 Channel Equalization and PPSNR Calculation

Since the received signal vector components are linear mixtures of the transmitted signal vector components plus white noise, a blind channel equalization method is needed to recover the transmitted streams from their noisy linear combinations.

Independent Component Analysis (ICA) [8], which is used in this study, is the conventional method for solving this problem. However, the ICA in this work is followed by Minimum Mean Square Error (MMSE) based equalization as in [9] to cope with residual interference.

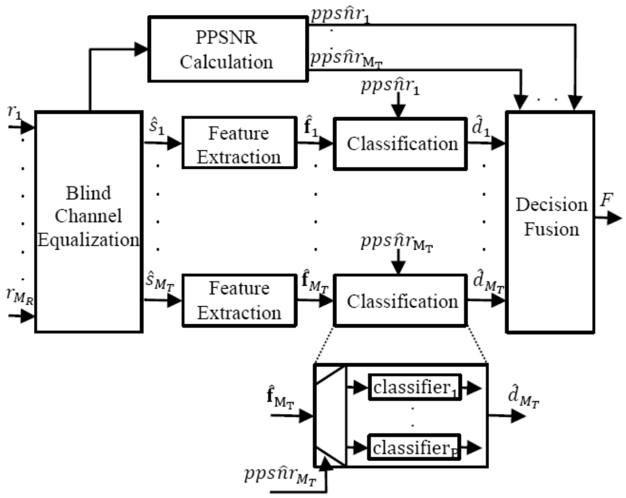

Fig. 1: A block diagram of the proposed AMC algorithm.

Several algorithms based on different criteria have been proposed so far to perform ICA, such as Joint Approximate Diagonalization of Eigen-matrices (JADE) [10] and Fast ICA [11]. A comparison study between these algorithms reported in [12]. Dues to its fast convergence speed, and satisfactory separation performance in many applications [13,14], the well-known JADE algorithm [10] 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. It is clear that permutation has no effect on the overall AMC performance since the ordering is not that important for the AMC algorithms [5]. However, the phase ambiguity inherited from JADE should be taken into consideration in the next stage when choosing the features; otherwise a phase correction technique is needed [5].

In practice, in order to cope with residual interference from other estimated streams, MMSE-based equalization is usually employed after JADE algorithm [9]. Thus, an initial channel estimate $\widehat{\mathbf{H}}$ is first obtained with JADE. Then, the equalization matrix $\mathbf{W}_M$ is found from the common MMSE criterion as [15]:

$$\mathbf{W}_M = (\widehat{\mathbf{H}}^H\, \widehat{\mathbf{H}} + \sigma_n^2\, \mathbf{I}_{M_T})^{-1}\, \widehat{\mathbf{H}}^H \tag{2}$$

Then, the estimated transmitted symbol vector at time instant k can be expressed as [15]:

$$\widehat{\mathbf{s}}(k) = \mathbf{W}_M\, \mathbf{r}(k) \tag{3}$$

At the output of the MMSE equalization, the residual signal plus interference from other estimated streams can be well approximated as Gaussian [15], and the PPSNR for each estimated transmit signal stream can be calculated; the PPSNR corresponding to the i^{th} $(1 \le i \le M_T)$ stream can be given as (considering that the transmitted signals have unity average power) [15]:

$$pps\widehat{n}r_i = \frac{|(\mathbf{W}_M\widehat{\mathbf{H}})_{i,i}|^2}{\Sigma_{l\neq i}|(\mathbf{W}_M\widehat{\mathbf{H}})_{i,l}|^2 + \sigma_n^2(\mathbf{W}_M\mathbf{W}_M^H)_{i,i}} \tag{4}$$

Where $(\cdots)_{i,l}$ denotes the $(i,l)^{th}$ entry and $(\cdots)_{i,i}$ denotes the i^{th} diagonal element of the matrix of interest. Note that the phase ambiguity inherited from JADE has no effect on the PPSNRs for the estimated streams.

3.2 Features Extraction

For each of M_T the transmit signal streams estimated in the first stage, the feature extraction is performed in this stage of the proposed algorithm as shown in Fig. (1), where a set of discriminative features for modulation classification is considered.

Previous research studies conducted in the field of modulation classification [16,17] showed that Higher Order Cumulants (HOCs) of the intercepted signal can be considered as one of the best candidate features for modulation classification in SISO [16] and also MIMO systems [17]. This is due to their robustness to phase rotation, resistance to additive Gaussian noise, and easiness to implementation [16].

In this study, only two HOCs are extracted and used as discriminating features; they are the normalized fourth-order cumulant ($\widetilde{C}_{42}$) and the magnitude of the normalized eighth-order cumulant ($|\widetilde{C}_{80}|$). These features are chosen since they are robust to phase rotation which in our study corresponds to the phase ambiguity inherited from JADE. Additionally, they are capable to reliably characterize the modulated signals considered in this study [16,17].

For a zero-mean random variable x, associated with a stationary random process for the data sequence $x(k)$, the $\widetilde{C}_{42}$ and $|\widetilde{C}_{80}|$ can be respectively defined as [18,19,20]:

$$\widetilde{C}_{42} = \frac{E(|x|^4) - |E(x^2)|^2 - E^2(|x|^2)}{E^2(|x|^2)} \tag{5}$$

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

Where $E(\cdot)$ is the statistical expectation operator.

Table (1) presents the theoretical values of $\widetilde{C}_{42}$ and $|\widetilde{C}_{80}|$ computed over the ideal noise-free channels for the modulated signals of interest.

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

-	BPSK	QPSK	8-PSK	16-PSK	16-QAM	64-QAM
$\widetilde{C}_{42}$	-2	-1	-1	-1	-0.68	-0.619
$\lvert\widetilde{C}_{80}\rvert$	272	34	1	0	13.988	11.502

3.3 SVM Based Classification

Based on the extracted features, the classification stage is performed in the third stage of the proposed algorithm to estimate the modulation type for each estimated transmit signal stream as depicted in Fig. (1).

Among many classification methods proposed so far, the Support Vector Machine (SVM) method has shown superior performance in the context of modulation classification [21]. This is due to its significant characteristics such as good generalization capability and powerful learning ability [21]. Thus, a multiclass SVM-based classifier is used in this study to estimate the modulation type for each estimated transmit signal stream.

Furthermore, since the extracted HOC features are dependent not only on the modulation type but also on the SNR, we propose to partition the entire SNR range into consecutive intervals. Additionally, we utilize a particular multiclass SVM for each SNR interval rather than utilizing a single multiclass SVM for the entire SNR range, so that more robust and reliable decisions can be made.

Thus, a multi-classifier classification system is utilized for each estimated stream; where each sub-classifier is a multiclass SVM trained at a specific SNR range. Based on the PPSNR value at the estimated stream, the sub-classifier trained at the range that includes this value is employed to estimate the modulation type for this stream. If the PPSNR is found to be out of the entire SNR range, then the sub-classifier trained at the closest SNR interval is utilized.

3.4 Decision Fusion

After classification of the modulation scheme at each estimated stream, the estimated decision $\widehat{d}_i$ $(1 \leq i \leq M_T)$ and its associated PPSNR estimation $pps\widehat{n}r_i$ $(1 \leq i \leq M_T)$ for each stream are fed to the FC-as depicted in Fig. (1).

Depending on the decision estimation vector $\widehat{\mathbf{d}} = [\widehat{d}_1, \widehat{d}_2, ..., \widehat{d}_{M_T}]$ and its associated PPSNR estimation vector $\mathbf{pps\widehat{n}r} = [pps\widehat{n}r_1, pps\widehat{n}r_2, ..., pps\widehat{n}r_{M_T}]$, we propose a decision fusion scheme based on the ML criterion. The proposed fusion scheme generates the final classification decision F; F is regarded as the most probable reason behind the observed decisions under their associated PPSNR conditions. Here, we assume that the classification probability matrices for the observed interval of PPSNR, also referred to as confusion matrices, are available at the FC. These matrices can be computed during the SVM training phase.

Let $\mathbf{M} = [mod_1, \;\; mod_2, ..., \;\; mod_m]$ denote the modulation set of interest; then the probability of making a modulation scheme mod_k $(1 \leq k \leq m)$ as a final decision F $(F \in \mathbf{M})$ given the observed decision $\widehat{\mathbf{d}}$ under the post-processing SNR condition $\mathbf{pps\widehat{n}r}$, denoted as $P(F = mod_k|(\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r}))$, can be computed using the Bayes rule as [22]:

$$P(F = mod_k|(\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})) = \frac{P((\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})|F = mod_k).P(F = mod_k)}{P(\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})} \tag{7}$$

Where $P((\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})|F = mod_k)$ is the probability of taking the decision $\widehat{\mathbf{d}}$ under the post-processing SNR condition $\mathbf{pps\widehat{n}r}$ given that the modulation scheme mod_k is the final decision F; $P(F = mod_k)$ is the prior probability of modulation scheme mod_k which is the same for all the considered schemes by assuming a uniform distribution for the prior probabilities; and $P(\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})$ is the probability of taking the decision $\widehat{\mathbf{d}}$ under the post-processing SNR condition $\mathbf{pps\widehat{n}r}$ which is the same for each modulation scheme mod_k.

Since the modulation scheme is estimated independently for each of the M_T streams, the probability $P((\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})|F = mod_k)$ can be expressed as:

$$P((\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})|F = mod_k) = \prod_{i=1}^{M_T} P((\widehat{d}_i, pps\widehat{n}r_i)|F = mod_k) \tag{8}$$

Where $P((\widehat{d}_i, pps\widehat{n}r_i)|F = mod_k)$ is the probability of taking the decision $\widehat{d}_i$ at the i^{th} estimated transmit signal stream under the post-processing SNR condition $pps\widehat{n}r_i$ given that the modulation scheme mod_k is the final decision F; this probability can be obtained from the confusion matrices.

After finding conditional probability $P((\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})|F = mod_k)$ for each candidate modulation scheme mod_k, the ML criterion is employed to find the final classification decision F:

$$\begin{aligned} F &= \underbrace{argmax}_{mod_k}\{P(F = mod_k|(\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})\} \\ &= \underbrace{argmax}_{mod_k}\left\{P\left((\widehat{\mathbf{d}}, \mathbf{pps\widehat{n}r})|F = mod_k\right)\right\} \end{aligned} \tag{9}$$

4 Results and discussion

Extensive Monte Carlo (MC) simulations were conducted in MATLAB to evaluate the performance of the proposed algorithm.

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

First, for each considered modulation scheme and SNR value in the range -10 to 15 dB, one hundred signal realizations were generated. Each realization consisted of $2048 \times M_T$ data symbols considering the following MIMO antenna configuration $M_T = 2$, $M_R = 4$. For each processed signal, the features were calculated according to Eqs. (5) and (6), combined to form the feature vectors. These realizations were employed only to train the multi-class SVM which was implemented using the LIBSVM package [23] and also produce the confusion matrix for each SNR. The SVM kernel function was studied empirically and the best performance was obtained when using the Radial Basis Function (RBF) as a kernel function. The one-against-all scheme was used to extend SVM to multi-class case due to its low complexity and good accuracy.

The considered SNR range (-10 to 15 dB) was partitioned into ten consecutive intervals with an equal width of 2.5 dB chosen experimentally after intensive simulations as a reasonable compromise between performance and complexity. Accordingly, the classification system for each estimated transmit signal stream was composed of ten classifiers; each of them was trained to be utilized under a specific SNR interval.

The classification performance of the proposed algorithm was evaluated in terms of probability of correct classification (P_{cc}) averaged over all the six considered modulation schemes and over a large number of trials. One thousand MC trials were performed for each modulation scheme (i.e., 6000 MC trials in total) where P_{cc} was obtained as the ratio of the number of trials at which the modulation scheme had been correctly classified to the total number of trials (i.e., 6000 trials). For all MC trials, unless otherwise mentioned, $N = 2048$ i.i.d symbols per transmit antenna was considered as an observation interval and $M_T = 2$, $M_R = 4$ as MIMO antenna configuration.

Fig. (2) illustrates the effect of the observation interval length N (i.e., number of the considered symbols) on the average P_{cc} over a wide range of SNRs; where M_T is set to 2, and M_R to 4 antennas. As expected, the algorithm performance improves as the observation interval length increases. This is because, as N increases, the reliability and accuracy of the HOC estimates also increase, leading to a significant improvement in the classification performance. For instance, at SNR equal to 10 dB, the average P_{cc} = 92%, 95%, and 98% for the respective N = 512, 1024, and 2048, whereas it reaches 100% for N = 4096. Note that the average P_{cc} does not quite approach 100% for N = 512 and 1024, even with a 15 dB SNR.

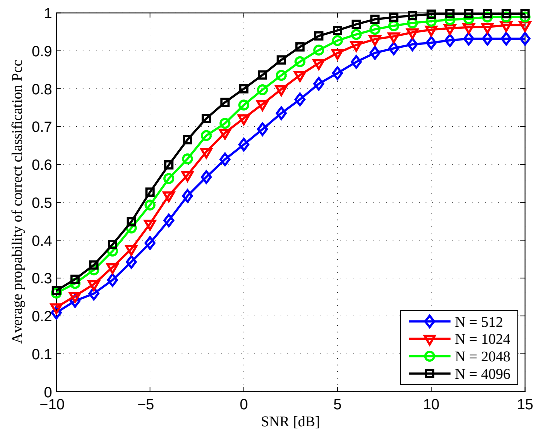

Fig. 2: Average probability of correct classification versus SNR for different observation interval lengths.

Fig. (3) shows the average P_{cc} achieved with the proposed algorithm for different MIMO antenna configurations over a wide range of SNRs where M_T is set to 2, and M_R to 4, 6, and 8 respectively. As noticed, the algorithm performance improves as the difference $(M_R - M_T)$increases. This is because as the difference $(M_R - M_T)$ increases, the diversity gain also increases, leading to a degradation in the symbol error probability [6] and accordingly an improvement in the overall algorithm performance. Note that the average P_{cc} reaches 90% for all the considered MIMO antenna configurations when SNR is not lower than 4dB.

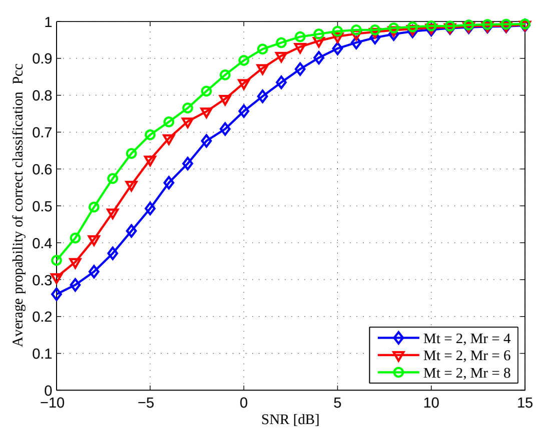

Fig. 3: Average probability of correct classification versus SNR for different MIMO antenna configurations.

Fig. (4) compares the performance of the proposed algorithm to its performance when employing the multi-classification method in [7] (using the multiclass

SVM as a sub-classifier and same SNR intervals) or only a single classifier trained at all SNR values as a classification system; where M_T is set to 2, and M_R to 4 antennas. As seen, the performance when adapting the classifier at each estimated transmit signal stream to the PPSNR at that stream is clearly better than that when adapting the classifiers to the average SNR at the receiver or when utilizing only a single classifier at each stream. For instance, at average P_{cc} equal to 90%, the proposed classification system offers SNR gain of about 2 dB when compared to the classification method proposed in [7] for $M_T = 2$ and $M_R = 4$ antennas.

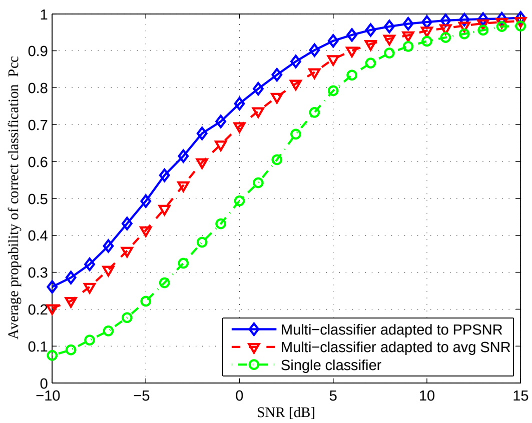

Fig. 4: Average probability of correct classification versus SNR at different classification scenarios.

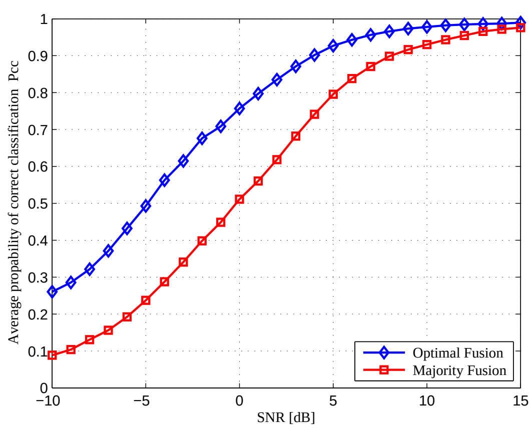

Fig. 5: Average probability of correct classification versus SNR at different fusion scenarios.

Fig. (5) compares the performance of the proposed algorithm with the suggested decision fusion rule to its performance when employing the conventional majority rule (M-out-of-M_T rule where $M = M_T/2$) as a fusion scheme; where M_T is set to 2, and M_R to 4. As clearly noticed, the performance when employing the proposed decision fusion is significantly better than that when employing the conventional majority decision fusion, especially at the low SNR region. For instance, at average P_{cc} equal to 90%, the proposed decision fusion offers SNR gain of about 3 dB when compared to the majority decision fusion. Moreover, it should be mentioned here that for the case when the majority fusion condition was not satisfied, the result was not considered as false alarm; hence, the majority fusion rule performance can become much worse.

5 Conclusion

In this paper, a robust and reliable feature-based AMC algorithm for spatially multiplexed MIMO systems is proposed. We have shown that adapting the classification system at each estimated transmit signal stream to the PPSNR at that stream significantly improves the classification performance in the context of the feature-based AMC algorithms for MIMO systems. We also addressed the problem of the decision fusion for the feature-based AMC algorithms and introduced an optimal decision fusion scheme based on the ML criterion in order to reach more accurate and reliable final classification decisions. The proposed algorithm showed a good classification performance under different operating conditions, without any prior information about the channel state.

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