Asynchronous Digital Amplitude–Phase Modulation Classifier in Flat Fading Channels using the SUI-3 Channel Model

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***Abstract*-This paper presents the implementation of SUI-3 Channel Model on an Asynchronous Digital Amplitude–Phase Modulation Classifier in Flat Fading Channels. In this classifier, we use a SUI-3 channel to transmit a signal and find the estimates for the unknown amplitude, time offset, and noise power that are blind to the modulation scheme of the received signal. It is shown that the classifier using SUI-3 channel model performs well compared to the optimal classifier with decreased mean square error (MSE) and we observe the probability of correct classification of the received signal.**

Index Terms - Modulation classification, SUI-3 Channel Model, Channel state information, Delay estimation.

I. INTRODUCTION

Asynchronous modulation classification is a process of finding out the type of modulation scheme used at the receiver end where the receiver does not have any idea about the transmitter's modulation scheme. In this paper, we use an asynchronous likelihood based (LB) modulation classifier for digital amplitude-phase modulated (PSK, QAM) signals in flat-fading channels developed in [1]. There are two main approaches to modulation classification, namely feature-based and likelihood-based (LB) [2]. In Likelihood-based classification, unknown received signal parameters must be handled with no knowledge of the modulation scheme. The classifier assumes no prior knowledge of the channel state (gain, time offset, phase shift, and noise level). Although asynchronous and synchronous LB classifiers have been developed for this class of signals in [1],[3] and [6]-[10], SUI-3 channel model parameters have not yet been used to transmit these signals.

SUI channels are the set of 6 specific channels models,3 terrain types , a variety of Doppler spreads , delay spread , line of sight and non-line of sight as given in table 1 [4]. The set of SUI channel models specify statistical parameters of microscopic effects (tapped delay line, fading, antenna directivity). Each set model also defines an antenna correlation and the gain reduction factor (GRF) has also been included to indicate the connection with the K- factor. Fig.1 shows how a signal is transmitted using a SUI channel.

Table 1: SUI Channel Models

Channel	Terrain Type	Doppler Spread	Delay Spread	LOS
SUI-1	C	Low	Low	High
SUI-2	C	Low	Low	High
SUI-3	B	Low	Low	Low
SUI-4	B	High	Moderate	Low
SUI-5	A	Low	High	Low
SUI-6	A	High	High	Low

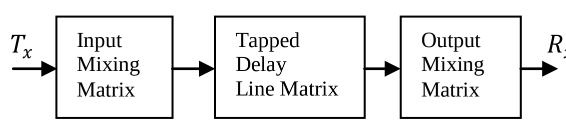

Fig 1. T_x and R_x block diagram of SUI Model

Channel State Information (CSI) refers to the known channel properties of a communication link. It describes how a signal propagates from the transmitter to the receiver and includes the amplitude, time offsets, phase shifts and noise power .CSI needs to be estimated at the receiver and usually quantized and fed back to the transmitter. In general, radios without complete knowledge of the received signal's modulation scheme must first classify the desired signal before they can synchronize with the received symbols and estimate the channel.

In this paper, we implement SUI-3 channel model parameters [5] on an asynchronous likelihood based (LB) modulation classifier for digital amplitude-phase modulated (PSK, QAM) signals in flat-fading channels. These parameters include the delay, power, K-factor, doppler spread, antenna correlation, gain reduction factor and the normalization factor of the transmitted signal. This new classifier assumes no prior knowledge of the channel state (gain, time offset, phase shift, and noise level).

During the implementation of the SUI-3 Channel model for the classifier, we use method-of-moments estimators for the unknown amplitude, time offset, and noise power, each of which is blind to the modulation format (PSK, QAM, etc) and modulation order of the received signal [1] and [6].

II.SYSTEM MODEL

The SUI-3 channel parameters have been used to transmit signals with N number of independent random samples. The parameters include the number of taps of the Doppler filter, observation rate, doppler resolution of SUI parameter, power in each tap, rician factor, delay, Doppler frequency, antenna correlation and gain normalization factor. Assuming that the transmitted signal passes through a flat fading channel, the signal $r(t)$ can be written from [1] as

$$s(\xi) = R\left\{A_t \sum_{k=-\infty}^{\infty} S_k\, g(\xi - kT)e^{j\omega_c \xi}\right\}, \qquad (1)$$

where A_t is the transmitter gain, S_k is the modulated data symbol, $g(\cdot)$ is the (real-valued) pulse shape, T is the symbol interval, and $\omega_c = 2\pi f_c$ where f_c is the carrier frequency. The symbols S_k, assumed to be normalized to unit average power without loss of generality, are taken from a (complex) symmetric constellation that defines the modulation scheme used. The pulse shape is assumed to have unit energy, without loss of generality, and to satisfy the Nyquist intersymbol interference criterion.

We now implement the SUI-3 channel model given in Table 2. to transmit the signal [5].

Table 2:SUI-3 Channel Model Definition

SUI-3 Channel				
	Tap 1	**Tap 2**	**Tap 3**	**Units**
Delay	0	0.5	1	μs
Power (omni ant.) **K Factor (omni ant.)**	0 1	-5 0	-10 0	dB
Power (30o ant.) **K Factor (30o ant.)**	0 3	-11 0	-22 0	dB
Doppler	0.4	0.4	0.4	Hz

Antenna Correlation: ρ_{ENV} = 0.4
Gain Reduction Factor: GRF = 3 dB
Normalization Factor: F_{omni} = -1.5113 dB,F30° = -0.3573 dB

We use the method of filtered noise to generate channel coefficients with the specified distribution and spectral power density. For each tap a set of complex zero-mean Gaussian distributed numbers is generated with a variance of 0.5 for the real and imaginary part, so that the total average power of this distribution is 1. This yields a normalized Rayleigh distribution (equivalent to Rice with *K*=0) for the magnitude of the complex coefficients. If a Rician distribution (*K*>0 implied) is needed, a constant path component *m* has to be added to the Rayleigh set of coefficients. The ratio of powers between this constant part and the Rayleigh (variable) part is specified by the *K*-factor. For this general case, we show how to distribute the power correctly by first stating the total power *P* of each tap:

$$P=|m|^2+ \sigma^2 , \qquad (2)$$

where *m* is the complex constant and σ^2 the variance of the complex Gaussian set. Second, the ratio of powers is:

$$K= \frac{|m|^2}{\sigma^2}, \qquad (3)$$

From (2) and (3), we can find the power of the complex Gaussian and the power of the constant part as:

$$\sigma^2 = P\frac{1}{K+1} \ and \ |m|^2 = P\frac{K}{K+1}, \qquad (4)$$

From (4), we can see that for *K*=0 the variance becomes *P* and the constant part power diminishes, as expected. Note that we choose a phase angle of 0° for *m* in the implementation.

The random components of the coefficients generated in the previous paragraph have a white spectrum since they are independent of each other. The SUI channel model defines a specific power spectral density (PSD) function for these scatter component channel coefficients called 'rounded' PSD which is given from [5] as:

$$S(f) = \begin{cases} 1 - 72f_0^2, & f_0 \le 1 \\ 0, & f_0 > 1 \end{cases} \qquad (5)$$

where $f_0 = \frac{f}{f_m}$

To arrive at a set of channel coefficients with this PSD function, we correlate the original coefficients with a filter which amplitude frequency response is written from (5) as

$$|H(f)| = \sqrt{S(f)} \qquad (6)$$

The SUI channel model also define an antenna correlation, which has to be considered if multiple transmit or receive elements, i.e. multiple channels, are being simulated. Antenna correlation is commonly defined as the envelope correlation coefficient between signals received at two antenna elements.

In the general case of frequency selective (delay-spread) propagation, the channel is modeled from [5] as a tapped-delay line:

$$g(t,\tau)=\sum_{l=1}^{L} g_l(t)\rho(\tau-\tau_l), \quad (7)$$

where L is the number of taps, $g_l(t)$ are the time-varying tap coefficients and τ and τ_l are the tap delays.

We define all the simulation parameters which include number of independent random realizations, observation rate in Hz, number of taps of the Doppler filter, Doppler resolution of SUI parameter in Hz (used in resampling-process) and accuracy of resampling process. Then, we define the SUI-3 Channel parameters which include power in each tap in dB, rician K-factor in linear scale, tap delay in µs, Doppler maximal frequency parameter in Hz, antenna correlation (envelope correlation coefficient)and gain normalization factor in dB.

We calculate the power in the constant and random components of the Rice distribution for each tap which includes the linear power P ($P=10^{\frac{P}{10}}$), variance σ,constant power (a function of linear power and ricean K-factor) and a constant part (square root of constant power).Now, we create the Rician channel coefficients with the specified powers and the coefficient sets which is a function of the number of taps (L) and the number of independent random realizations (N).

Before combining the coefficient sets, the white spectrum is shaped according to the Doppler PSD function (5). Since there are no frequency components higher than *fm*, the channel can be represented with a minimum sampling frequency of 2 *fm*, according to the Nyquist theorem. We therefore simply define that our coefficients are sampled at a frequency of 2 *fm*. The total power of the filter has to be normalized to one, so that the total power of the signal is not changed by it.

Now that the fading channel is fully generated, we have to apply the normalization factor and, if applicable, the gain reduction factor.

The received signal (ξ) is given from [1] by

$$R\left\{A_c A_t \sum_{k=-\infty}^{\infty} S_k\, g(\xi-kT-\xi_c)e^{j(\omega_c \xi+\theta)}\right\}, \quad (8)$$

where A_c,θ, and ξ_c are the gain, phase shift, and time delay introduced by the channel, respectively. It is assumed that the channel remains constant during the observation interval.

Let $\xi_c-\xi_0 = (\lambda+\nu)T$, where λ represents the integer number of symbols offset and ν represents the remaining fraction of a symbol offset ($0 \le \nu < 1$). Using this notation, (8) can be written as

$$r(t)=R\left\{\alpha \sum_{k=-\infty}^{\infty} S_k g(t-(k+\lambda+\nu)T)e^{j(\omega_c t+\theta)}\right\} + n(t), \quad (9)$$

where $\alpha = A_c A_t$ and $n(t)$ is a zero-mean Gaussian noise process with two-sided power spectral density $N_o/2$. Note that the phase shift due to the time reference change is incorporated into θ. The following assumptions about the received signal are used in the analysis that follows. The symbol S_k is uniformly distributed over the set of all possible constellation values of the modulation scheme used. The pulse shape g(·), the symbol interval T , and the carrier frequency f_c are assumed to be known. All other parameters, namely the amplitude α, phase shift θ, time offset ($\lambda+\nu$), and noise power N_o are modeled as deterministic unknown variables.

III.MODULATION CLASSIFIER

The classifier was developed in [1] based upon the output of a receiver that consists of a frequency conversion stage (from RF to baseband) and a matched filter. From (9), the output of the receiver at $t = (l+v)$, where l is an integer and v is a real number in the range [0, 1), is

$$r_{l,v} = \int_{-\infty}^{\infty} r(\tau)e^{-j\omega_c \tau} g\big((l+v)T-\tau\big)d\tau$$
$$=\frac{\alpha e^{j\theta}}{2}\sum_{k=-\infty}^{\infty} S_k R((l-\lambda+v-\nu-k)T) + n_{l,v}, \quad (10)$$

where $R(t)=\int_{-\infty}^{\infty} g(\tau)g(t-\tau)d\tau$ and $n_{l,\nu}$ is a zero-mean complex Gaussian random variable with variance $N_o/2$.In the classifier used, it was first assumed that the receiver has a perfect estimate of the fractional time offset v; that is, the receiver perfectly estimates when symbol transitions occur.

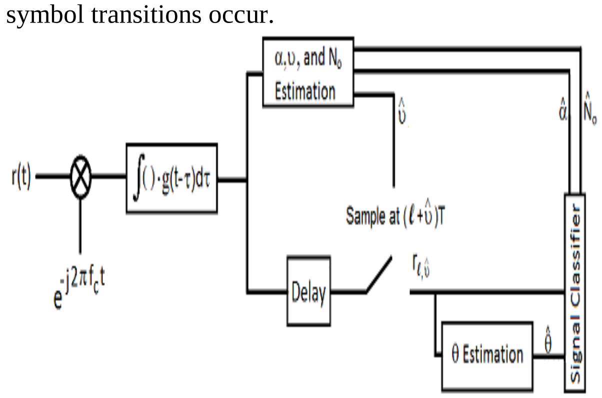

Fig. 2.An asynchronous qHLRT-based modulation classifier [1]

In this case, the vector $r_v = [r_{1,v}, r_{2,v}, \ldots\ldots, r_{N_c,v}]$ is a set of sufficient statistics for the detection of the symbols $S_{1-\lambda}, S_{2-\lambda}, \ldots., S_{N_c-\lambda}$.(Recall that λ is unknown) Given that the $r_{l,v}$, values are independent, the Total Probability Theorem Π can be used to show that

$$p(r_v|H_i) = \prod_{l=1}^{N_c}\sum_{m=1}^{L_i} p\left(r_{l,v}\middle|S_{m,i}, H_i)P(S_{m,i}|H_i)\right), \qquad (11)$$

where $S_{m,i}$ is one of the L_i complex constellation values of the ith modulation scheme. Taking the logarithm of $p(r_v|H_i)$, and using the fact that (10) reduces to $r_{l,v} = \frac{\alpha e^{j\theta}}{2} S_{l-\lambda} + n_{l,v}$ when $\nu = \nu$, the classifier can be written from [1] as

$$\hat{H} = \arg \underbrace{max}_{H_i} \sum_{l=1}^{N_c} \ln\left(\frac{1}{L_i}\sum_{m=1}^{l_i} p\left(r_{l,v}\middle|S_{m,i}H_i\right)\right)$$

$$= \arg \underbrace{max}_{H_i} \sum_{l=1}^{N_c} \ln\left(\frac{1}{L_i}\sum_{m=1}^{l_i} e^{\frac{2}{N_0}\left|r_{l,v}-\frac{\alpha e^{j\theta}}{2}S_{m,i}\right|^2}\right), (12)$$

Note that the classifier given by (12) is a function of α, θ, ν and N_0 . In order to handle these unknowns, we use a qHLRTbased approach. In this approach, the channel parameters are estimated through the use of low-complexity estimators that are blind to the modulation scheme of the received signal. This approach is used for two reasons. First, this approach does not require knowledge of the statistics of the channel parameters. Instead, these parameters are modeled as deterministic unknown variables. Second, this approach does not require multi-dimensional maximum-likelihood estimation of the parameters, leading to a lower complexity classifier.

Given that α, θ, ν, and N_o are unknown at the receiver, the qHLRT approach dictates that these values are replaced by their estimates (denoted by^). This leads to the final form of

$$\hat{H} = \arg \underbrace{max}_{H_i} \sum_{l=1}^{N_c} \ln\left(\frac{1}{L_i}\sum_{m=1}^{l_i} e^{\frac{2}{\hat{N}_0}\left|r_{l,\hat{v}}-\frac{\hat{\alpha} e^{j\hat{\theta}}}{2}S_{m,i}\right|^2}\right), \qquad (13)$$

where $i = 1, 2, \ldots, c$, for the proposed *asynchronous* qHLRT-based modulation classifier, where $r_{l,\hat{v}}$ is the output of the receiver given the sampling instant $(l + \hat{v})T$.

IV. ESTIMATION OF THE UNKNOWN RECEIVED SIGNAL PARAMETERS

After transmitting a signal through a SUI-3 channel model parameters, we need to calculate the estimates for the unknown amplitude, time offset, and noise power of the received signal. For this, an estimator that is blind to the signal's modulation format (PSK, QAM, or PAM) and order is used [Ref.1]. The estimators are based on a low-complexity estimation approach known as the Method-of-Moments (MoM). This is a suboptimal approach in which parameters are estimated through the solution of a system of statistical moment equations.

The first of these moments is $\left[\left|r_{l,v_1}\right|^2\right]$, where r_{l,v_1} is the output of the receiver at t = $(l + v_1)$T , l is an arbitrarily chosen integer, and v_1 is an arbitrarily chosen real number in the range (0, 1). Using (10) with $\nu = v_1$, the moment can be written as

$$M_{v1} = E[\left|r_{l,v_1}\right|^2 = \frac{\alpha^2}{4}\psi_{v_1,\nu} + \frac{N_o}{2}, \qquad (14)$$

assuming the data symbols are independent. In (14), the function $\psi_{v_1,\nu}$ is defined as

$$\psi_{v1,\nu} = \sum_{k=-\infty}^{\infty} R((l-\lambda+v_1-\nu-k)T)^2$$

$$= \sum_{k=-\infty}^{\infty} R((v_1-\nu-k')T)^2 , \qquad (15)$$

It is important to note that (14) is a function of the unknowns α, ν, and N_o while not being a function of the unknown data, or θ. Also, (14) is not a function of l, which implies that $E[\left|r_{l_1,v1}\right|^2$ and $E[\left|r_{l_2,v1}\right|^2$ are equal for all integers l_1 and l_2 . For this reason, $E[\left|r_{l,v_1}\right|^2 = M_{v_1}$.Assuming a square root-raised cosine pulse shape, $\psi_{v1,\nu}$ is equal to 1 +β/4 (cos(2$\pi(v_1 - \nu)$) − 1). Therefore, for this pulse shape, (14) can be rewritten as

$$N_o = 2M_{v_1} - \frac{\alpha^2}{8}\{4 + \beta(\cos(2\pi[\nu - v_1]) - 1\} \qquad (16)$$

Next, it is assumed that the receiver has a new sampling instant of $(l + v_2)$, where l is an arbitrarily chosen integer and v_2 is an arbitrarily chosen real number in the range [0, 1), with $v_2 \neq v_1$. (Note that l and v_2 have no relation to λ or ν.) Given this new sampling instant, a second equation for N_o can be determined from the moment $E[\left|r_{l,v_2}\right|^2 = M_{v_2}$ .Setting these two N_o equations equal, and performing some algebraic manipulation, gives

$$\alpha^2 = \frac{16(M_{v1} - M_{v2})}{\beta[\cos(2\pi(\nu - v_1)) - \cos(2\pi(\nu - v_2))]}, \qquad (17)$$

which is only a function of the unknowns α and ν.

The final step is to use a third moment equation to remove the dependence on one of the two unknowns of (17). Assuming a third sampling instant $(l + v_3)$, where again l is an arbitrarily chosen integer and v_3 is an arbitrarily chosen real number in the range [0, 1), with $v_3 \neq v_2 \neq v_1$, the moment $E[|r_{l,v_3}|^2 = M_{v_3}$ can be determined. (Note that l and v_3 have no relation to λ or ν.) Using this third moment with either of the previous two moments, a second equation for α^2 can be determined. Setting the two α^2 equations equal and performing some manipulation leads to (20), where $X_i = \cos(2\pi v_i)$ and $y_i = \sin(2\pi v_i)$ Inverting (20), and assuming that atan(Z) is in the range [$-\pi/2$, $\pi/2$], may assume one of three possible values,

$$v = \left\{\frac{\operatorname{atan}(Z)}{2\pi}, \frac{\operatorname{atan}(Z)}{2\pi} + \frac{1}{2}, \frac{\operatorname{atan}(Z)}{2\pi} + 1\right\}, \qquad (18)$$

Therefore, the unknowns α, ν, and N_o can be determined from the moments M_{v1} , M_{v_2} , and M_{v_3} . This is done by first using the moments to determine the three possible values for ν given by (18). One of the values can be immediately discarded for falling outside of the range $0 \leq \nu < 1$. Given the remaining two possible ν values, two possible values for α are determined through (17). Finally, the values for α and ν are used to determine N_o through (16). In practice, the moments M_{v1} , M_{v_2} , and M_{v_3} are unknown and thus must be estimated from the received signal. This estimation can be done using the simple sample average estimator

$$\widehat{M_{v_i}} = \frac{1}{N_{est}} \sum_{l=l_i}^{l_i+N_{est}} |r_{l,vi}|^2, \; i = 1,2,3, \qquad (19)$$

where r_{l,v_i} is the receiver output sampled at $(l + v_i)T$, Nest is the number of samples observed, and l_i is an arbitrary integer. Therefore, given that the moments themselves are estimated, the solutions to (16), (17) and (18) are estimates for the parameters N_o, α, and v respectively. In order to estimate θ, a MoM-based algorithm known as the M-power phase synchronizer is used, which is also blind to the received signal's modulation scheme. This estimator uses a sample average estimator for the Mth moment of the outputs $r_{l,\hat{v}}$. For example, for PSK schemes, the estimator is

$$\hat{\theta}_{M-PSK} = \frac{1}{M} \arg\left\{\sum_{l=1}^{N_c} r_{l,\hat{v}}^M\right\}$$

where M is the order of the modulation scheme assumed. For QAM scheme

$$\hat{\theta}_{QAM} = \frac{1}{4} \arg\left\{\sum_{l=1}^{N_c} r_{l,\hat{v}}^4\right\}$$

$$\tan(2\pi v) = \frac{(M_{v_3} - M_{v_2})X_1 + (M_{v_1} - M_{v_3})X_2 + (M_{v_2} - M_{v_1})X_3}{(M_{v_2} - M_{V_3})Y_1 + (M_{v_3} - M_{v_1})Y_2 + (M_{v_1} - M_{v_2})Y_3} = Z, \qquad (20)$$

V.PERFORMANCE ANALYSIS

The asynchronous modulation classifier is shown in Fig.2.SUI-3 Channel Model was used to decrease the path loss and improve the performance of the classifier where the signal was QPSK modulated. After this, we found the estimates for the amplitude (α), time offset (ν) and noise power (N_o).Then, these estimates were compared with their true values to calculate their mean square error and the average probability of correct classification of the received signal.

The values of v_1, v_2 and v_3 are equal to 0.1,1/3 and 2/3 respectively. The unknown values of amplitude α was assumed to be Rayleigh distributed with E[α^2]=1.Fig.3 presents the performance of the MoM estimators of the old model used from [1] for a square root-raised cosine pulse with roll-off factor of β = 0.35. Fig.4 presents the performance of the MoM estimators after using a SUI-3 channel for a square root-raised cosine pulse with roll-off factor of β = 0.35.As expected, for both these models, as the SNR and/or N_{est} was increased, the average mean square error (MSE) of the estimates decreases and this decrease in MSE with respect to SNR was greater after using the SUI-3 Channel. The decrease in MSE in fig.3 and fig.4 is because an increase in either of these parameters reduces the estimation error of M_{v_1} , M_{v_2} , and M_{v_3}. Additionally, it was seen that the average MSE of the estimates increases for lower roll-off factors. This is due to the fact that timing offsets result in larger intersymbol interference for lower roll-off factors, leading to an overall reduction in the performance of the estimators. Fig.5 presents the average probability of correct classification of the MoM estimators after using the SUI-3 channel for a square root-raised cosine pulse with roll-off factor of β = 0.35 and β=0.75 with the number of samples used as 500 and 1000.Fig. 6 presents the average probability of correct classification for the case in which the roll-off factors of the pulse shaping filters at the transmitter and receiver are mismatched. It was observed that the average probability of correct classification increases with the increase in signal to noise ratio.

The performance also improved with the increase in the number of samples used and the roll-off factors. The decrease in the mean square error means that the estimated values of the amplitude, time offset and noise power approach closer to their true values. Average probability of correct classification of the transmitted signal at the receiver improves and optimum performance of the classifier can hence be obtained.

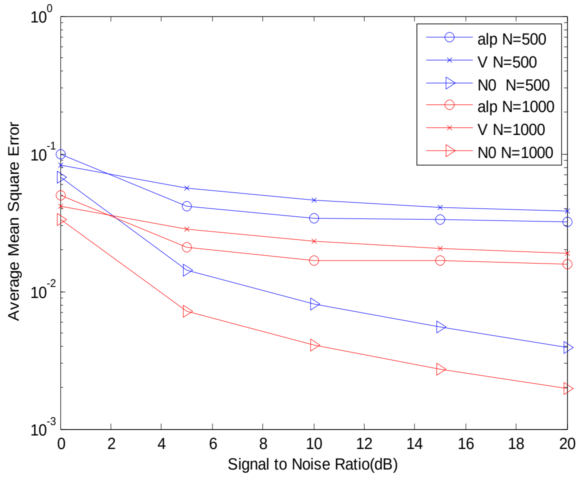

Fig 3.Average MSE given a square root-raised cosine pulse shape (Blue:N_{est} = 500 , Red:N_{est} =1000) of the old model [1]

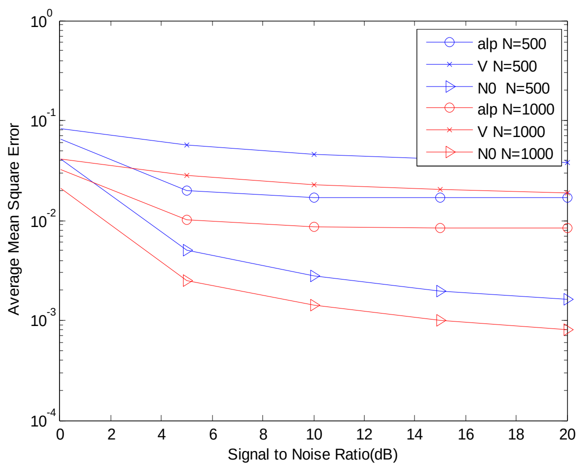

Fig.4.Average MSE given a square root-raised cosine pulse shape (Blue:N_{est} = 500 , Red:N_{est} =1000) using the SUI-3 channel model

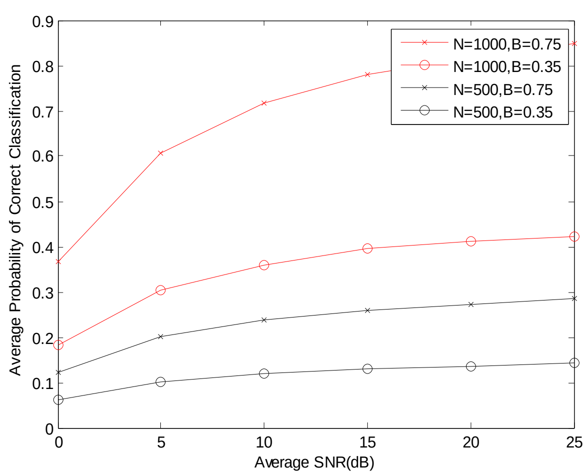

Fig.5. Average probability of correct classification given a Rayleigh fading model (N_c = 500) using the SUI-3 channel model

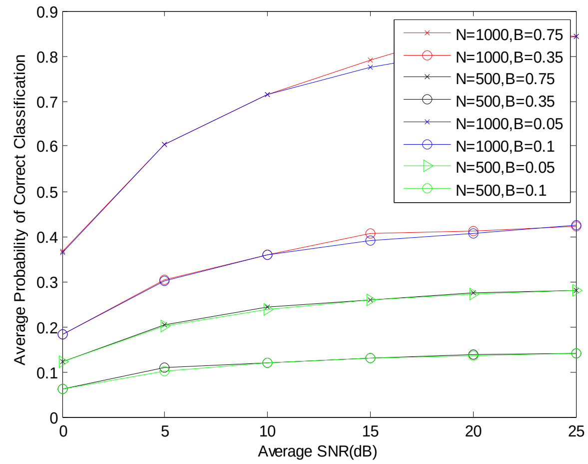

Fig. 6. Average probability of correct classification for the case in which the roll-off factors of the pulse shaping filters at the transmitter and receiver are mismatched (N_{est} = 10000, N_c= 500, solid: β = 0.75, dashed: β = 0.35) using the SUI-3 channel model

VI. CONCLUSIONS

A modulation classifier, that assumes no prior knowledge of the channel state, was used for digital amplitude-phase modulated signals in flat-fading channels [1].Modulation classification is a challenging problem as it requires channel information for optimal performance. In order to estimate the unknown amplitude, time offset, and noise power of the received signal for use in the classifier, MoM estimators were used that are blind to the received signal's modulation scheme.SUI-3 Channel was used to transmit a signal that was QPSK modulated through constant and random paths of Rayleigh and Rician fading models. We observed the decrease in MSE with respect to SNR of amplitude (α), time offset (v) and noise power (N_o) for different number of samples used and found out that the use of SUI-3 channel model parameters reduces the MSE to a greater extent as compared to the old model used in [1].We also observed that average probability of correct classification of the received signal increases with the increase in the number of samples (N) and roll-off factors (β) of the estimates. Thus, the overall performance of the modulation classifier improves.

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