SNR Estimation of QAM-Modulated Transmissions over Time-Varying SIMO Channels

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***Abstract*—We propose a new technique to estimate the signal-to-noise ratio (SNR) over flat fading time-varying single-input multiple-output (SIMO) channels, for quadrature amplitude modulation (QAM) signals in complex additive white Gaussian noise (AWGN). This technique relies on the use of periodically transmitted pilot symbols in the estimation process. It is a decision directed (DD) procedure since detected data symbols are also used. Performance is assessed via Monte Carlo simulations. Using the normalized root mean square error (NRMSE) as a measure of performance, our new estimator performs well over a wide SNR range.**

I. INTRODUCTION

With the rapid development of some new applications for modern communication systems, an intense search for an accurate and low complexity SNR estimator has been made over the last few decades. For example, The SNR knowledge is often a requirement when dealing with, for instance, transmit power control, adaptive modulation, handoff, dynamic allocation of resources or soft decoding procedures [1, 2]. Methods, that rely on known transmitted data to estimate the SNR, are called data-aided (DA) methods. Those which do not require any a priori knowledge of the transmitted symbols are called non-data-aided (NDA). A subcategory of DA methods, the decision-directed (DD) techniques, base the estimation process on detected transmitted symbols. Researchers have mainly focused on SNR estimation over flat fading [3, 4] and frequency selective [5, 6] channels that could be assumed constant over the observation interval. However, most of the derived methods are not applicable when the channel is time-varying. In fact, even small time variations over the estimation interval can dramatically degrade the performance of traditional, constant channel, SNR estimators. An iterative SNR estimation technique over flat fading time-varying channels was introduced by Wiesel [7]. However, this method is only applicable for Phase Shift Keying (PSK) signals. In fact, to the best of our knowledge, the estimation/tracking of the instantaneous SNR over time-varying channels for non-constant envelope constellations has never been addressed before. Therefore, we will present, in this paper, a new method that estimates the SNR over flat fading time-varying SIMO channels with quadrature amplitude modulation (QAM) signals.

It should be noted that NDA methods are well suited for the estimation of the SNR of PSK signals transmitted over a channel that can be assumed time-invariant over the observation interval, because these methods can exploit the constant envelope property of the received signal. Furthermore, the estimation of the instantaneous SNR over a time-varying channel using a moment-based approach is problematic, even for PSK, because the required short-term estimates of the moments would often result in unacceptable accuracy. For transmitted signals with non-constant envelope (QAM signals that have no PSK equivalent), when the transmitted data sequence is unknown at the receiver, the estimation of the instantaneous SNR using data-aided methods is further complicated by the fact that different SNR estimate candidates exist for the different possible transmitted data sequences, even if the estimation is based on the envelope of the received signal.

Our new instantaneous SNR estimation technique will rely on the use of periodically transmitted pilot symbols. However, exploiting these pilot alone symbols would potentially provide us with an estimate of unacceptable accuracy if the received data symbols corresponding to those transmitted pilot symbols are too few and/or too noisy to allow for a precise tracking of the channel variations. Therefore, to improve its performance, our new SNR estimator includes a decision-directed strategy to also exploit data symbols. Since PSK pilot symbols can be selected in the system design, but non-PSK high order QAM data symbols are often desired for broadband systems, the SNR estimator is devised in such a way that it can be applied to systems that use any QAM constellation.

As there is no reported work on SNR estimation for QAM modulated signals under time-varying channels, and as it relies on the channel coefficients estimation, the performance of our newly derived estimator is compared to the SNR estimator that can be obtained using a basic channel estimation technique.

The remainder of this paper is organized as follows. We will begin by deriving the new SNR estimator. Then, we will derive an SNR estimator that can be directly obtained from a basic channel estimation procedure. Finally, via Monte Carlo simulations and using the NRMSE as a performance parameter, we will study the performance of our new DD method. We will see that the new technique can estimate accurately the SNR, and that, for a wide SNR range, it exhibits a performance similar to the one that could be achieved if all symbols were ideally known to the receiver. We will also show the clear superiority of our SNR estimator against the one based on an existing basic channel estimation method.

II. System model

Consider a digital communication system with a SIMO configuration. A frequency-flat time-varying fading channel is assumed. We also assume that all the noise components are modelled by complex white Gaussian variables, of equal average power. Assuming an ideal receiver with perfect synchronization and considering the antenna element i, the input-output baseband relationship can be written as

$$y_i(n) = a(n)h_i(n) + w_i(n), \quad n = 1, 2, \ldots, N, \tag{1}$$

where, at time index n, $a(n)$ is the n^{th} transmitted symbol and $y_i(n)$ is the corresponding received sample. $h_i(n)$ is the time-varying channel gain and $w_i(n)$ is a realization of a zero-mean AWGN of variance σ^2. These received samples can be written in the following $N \times 1$ vectorial form:

$$\boldsymbol{y}_i = \boldsymbol{A}\boldsymbol{h}_i + \boldsymbol{w}_i, \quad i = 1, 2, \ldots, N_a, \tag{2}$$

where

$$\boldsymbol{y}_i = [y_i(1), y_i(2), \cdots, y_i(N)]^T, \tag{3}$$
$$\boldsymbol{h}_i = [h_i(1), h_i(2), \cdots, h_i(N)]^T, \tag{4}$$
$$\boldsymbol{w}_i = [w_i(1), w_i(2), \cdots, w_i(N)]^T, \tag{5}$$
$$\boldsymbol{A} = \text{diag}\{a(1), a(2), \cdots, a(N)\}, \tag{6}$$

where the superscript T stands for the transpose operator and N denotes the total number of received symbols. In the estimation interval, the SNR estimation problem may be stated as follows. Given some known symbols (pilot symbols) and the observation vector $\boldsymbol{y}_i$, estimate the SNR, over each antenna element i, which is given by

$$\rho_i = \frac{\sum_{n=1}^{N} |h_i(n)|^2 |a(n)|^2}{N\sigma^2}. \tag{7}$$

Most of the existing SNR estimation methods suppose that the channel is highly correlated and can be assumed constant during the observation interval. However, as shown in [7], even small variations from these assumptions can dramatically degrade their performance. An appropriate model for the time-variations of the channel coefficients is polynomial in time [8, 9]. Accordingly, the channel coefficients for a given antenna element i can be written as

$$h_i(n) = \sum_{m=0}^{L_c-1} c_{i;m} t_n^m + R_{i;L_c}(n), \tag{8}$$

where $c_{i;m}$ is the m^{th} polynomial coefficient for the channel at antenna branch i and t_n is the time index of the n^{th} sample (relative to the beginning of the estimation interval). The mean-squared value of the remainder $R_{i;L_c}(n)$ approaches zero as $L_c \to +\infty$ or as $(\frac{f_d}{f_s})N \to 0$ [9], where f_d and f_s are, respectively, the maximum Doppler and sampling frequencies. Therefore, in practice, for L_c sufficiently high or for $(\frac{f_d}{f_s})N \ll 1$, the channel can be locally approximated by a polynomial-in-time model, and one can therefore write:

$$h_i(n) = \sum_{m=0}^{L_c-1} c_{i;m} t_n^m, \quad n = 1, 2, \ldots, N. \tag{9}$$

Using eq. (9), and considering the entire observation interval, the channel can be conveniently represented in the following $(N \times 1)$ column vectorial form:

$$\boldsymbol{h}_i = \boldsymbol{T}_{L_c}\boldsymbol{c}_i, \tag{10}$$

where

$$\boldsymbol{T}_{L_c} = \begin{pmatrix} 1 & t_1 & \cdots & t_1^{L_c-1} \\ 1 & t_2 & \cdots & t_2^{L_c-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & t_N & \cdots & t_N^{L_c-1} \end{pmatrix}, \boldsymbol{c}_i = \begin{pmatrix} c_{i;0} \\ c_{i;1} \\ \vdots \\ c_{i;L_c-1} \end{pmatrix}. \tag{11}$$

Using eqs. (7) and (10), the SNR that we want to estimate can be written as

$$\rho_i = \frac{\boldsymbol{c}_i^H \boldsymbol{T}_{L_c}^T \boldsymbol{A}^H \boldsymbol{A} \boldsymbol{T}_{L_c} \boldsymbol{c}_i}{N\sigma^2}. \tag{12}$$

The superscript H stands for the Hermitian operator. Moreover, from now on, for ease of notation, we will omit the subscript L_c and we will simply refer to the matrix $\boldsymbol{T}_{L_c}$ by $\boldsymbol{T}$. We will also suppose that $N > L_c$.

III. Formulation of the new SNR estimator

The idea is to use all the received data over all the antenna elements in order to estimate the SNR on a given antenna branch. Indeed, using an array of antenna elements has the major advantage of providing us with a number of equations that can be sufficient to find all the desired unknowns in eq. (12).

In fact, on one hand, the unknowns of the problem are the N_a vectors $\{\boldsymbol{c}_i\}_{i=1,2,\ldots,N_a}$ and the N transmitted symbols $\{a(n)\}_{n=1,2,\ldots,N}$. Note that each vector $\boldsymbol{c}_i$ contains L_c unknowns $\{c_{i;m}\}_{m=1,2,\ldots,L_c}$, the coefficients of the channel corresponding to the antenna element i. The total number of unknowns is therefore $N_a L_c + N$. On the other hand, considering eq. (2) for $i = 1, 2, \ldots, N_a$, we see that we have NN_a independent equations. Hence, to be able to find all the unknowns, we need $NN_a \geq N_a L_c + N$, which means $N_a \geq \frac{N}{N-L_c} > 1$, since, in practice, N can be chosen sufficiently high. This is what justifies the effectiveness of the SIMO configuration choice in our procedure.

Using eqs. (2) and (10), the input-output relationship can be extended, with the presence of N_a antenna branches, to the following $(N \times N_a)$ matrix form

$$\boldsymbol{Y} = \boldsymbol{A}\boldsymbol{T}\boldsymbol{C} + \boldsymbol{W}, \tag{13}$$

where

$$\boldsymbol{Y} = [\boldsymbol{y}_1, \cdots, \boldsymbol{y}_{N_a}], \tag{14}$$
$$\boldsymbol{C} = [\boldsymbol{c}_1, \cdots, \boldsymbol{c}_{N_a}], \tag{15}$$
$$\boldsymbol{W} = [\boldsymbol{w}_1, \cdots, \boldsymbol{w}_{N_a}]. \tag{16}$$

Contrarily to the method introduced in [7], we will exploit the presence of $N_p > L_c$ pilot symbols in order to provide a non-iterative solution. Let $\boldsymbol{A}_p$ be the diagonal matrix that contains such N_p symbols and $\boldsymbol{T}_p$ be the corresponding time matrix. By writing $\boldsymbol{\Phi}_p = \boldsymbol{A}_p\boldsymbol{T}_p$, from eq. (13) we can write

$$\boldsymbol{Y}_p = \boldsymbol{\Phi}_p\boldsymbol{C} + \boldsymbol{W}_p, \tag{17}$$

where $\boldsymbol{Y}_p$ and $\boldsymbol{W}_p$ are, respectively, the received data and the noise components corresponding to the pilot symbols. In the least square (LS) sense, a first estimate $\widehat{\boldsymbol{C}}_p$ of $\boldsymbol{C}$ is given by

$$\widehat{\boldsymbol{C}}_p = (\boldsymbol{\Phi}_p^H\boldsymbol{\Phi}_p)^{-1}\boldsymbol{\Phi}_p^H\boldsymbol{Y}_p. \tag{18}$$

Injecting $\widehat{\boldsymbol{C}}_p$ in eq. (13), we can now estimate the matrix $\boldsymbol{A}$. In fact, by writing $\boldsymbol{\Phi}'_p = \boldsymbol{T}\widehat{\boldsymbol{C}}_p$, eq. (13) becomes

$$\boldsymbol{Y} = \boldsymbol{A}\boldsymbol{\Phi}'_p + \bar{\boldsymbol{W}}, \tag{19}$$

where $\bar{\boldsymbol{W}}$ contains the original noise components $\boldsymbol{W}$ and an additional noise which is due to the estimation of the matrix $\boldsymbol{C}$. In the LS sense, straightforward development yields the following expression for the estimate $\widehat{\boldsymbol{A}}$ of $\boldsymbol{A}$

$$\widehat{\boldsymbol{A}} = \boldsymbol{Y}\widehat{\boldsymbol{C}}_p^H(\widehat{\boldsymbol{C}}_p\widehat{\boldsymbol{C}}_p^H)^{-1}(\boldsymbol{T}^T\boldsymbol{T})^{-1}\boldsymbol{T}^T, \tag{20}$$

which, by writing $\boldsymbol{\Phi}'' = \widehat{\boldsymbol{A}}\boldsymbol{T}$ and injecting it in eq. (13), allows the recomputation of a refined estimate $\widehat{\boldsymbol{C}}$ of $\boldsymbol{C}$:

$$\widehat{\boldsymbol{C}} = (\boldsymbol{\Phi}''^H\boldsymbol{\Phi}'')^{-1}\boldsymbol{\Phi}''^H\boldsymbol{Y}. \tag{21}$$

The SNR estimate $\widehat{\rho}_i$, on the i^{th} antenna, is therefore given by

$$\widehat{\rho}_i = \frac{\widehat{\mathbf{c}}_i^H\boldsymbol{T}^T\widehat{\boldsymbol{A}}^H\widehat{\boldsymbol{A}}\boldsymbol{T}\widehat{\boldsymbol{c}}_i}{N\widehat{\sigma}^2}. \tag{22}$$

Then, injecting (20) and (21) in (13), noise components can be found as

$$\begin{aligned} \boldsymbol{w}_i &= \boldsymbol{y}_i - \hat{\boldsymbol{A}}\boldsymbol{T}\hat{\mathbf{c}}_i, &(23)\\ &= \boldsymbol{y}_i - \boldsymbol{\Phi}''\hat{\mathbf{c}}_i. &(24)\end{aligned}$$

Consequently, the noise power estimate is given by

$$\begin{aligned} N\hat{\sigma}^2 &= (\boldsymbol{y}_i - \boldsymbol{\Phi}''\hat{\mathbf{c}}_i)^H(\boldsymbol{y}_i - \boldsymbol{\Phi}''\hat{\mathbf{c}}_i), &(25)\\ &= (\boldsymbol{y}_i - \boldsymbol{P}\boldsymbol{y}_i)^H(\boldsymbol{y}_i - \boldsymbol{P}\boldsymbol{y}_i), &(26)\\ &= \boldsymbol{y}_i^H(\boldsymbol{I}-\boldsymbol{P})^H(\boldsymbol{I}-\boldsymbol{P})\boldsymbol{y}_i, &(27)\\ &= \boldsymbol{y}_i^H(\boldsymbol{I}-\boldsymbol{P})\boldsymbol{y}_i, &(28)\\ &= \boldsymbol{y}_i^H\boldsymbol{P}^{\perp}\boldsymbol{y}_i. &(29)\end{aligned}$$

Finally, the SNR estimate $\widehat{\rho}_i$, on the i^{th} antenna element, reduces simply to

$$\widehat{\rho}_i = \frac{\boldsymbol{y}_i^H\boldsymbol{P}\boldsymbol{y}_i}{\boldsymbol{y}_i^H\boldsymbol{P}^{\perp}\boldsymbol{y}_i}, \tag{30}$$

where, $\boldsymbol{P} = \widehat{\boldsymbol{A}}\boldsymbol{T}(\boldsymbol{T}^T\widehat{\boldsymbol{A}}^H\widehat{\boldsymbol{A}}\boldsymbol{T})^{-1}\boldsymbol{T}^T\widehat{\boldsymbol{A}}^H$ and $\boldsymbol{P}^{\perp} = \boldsymbol{I} - \boldsymbol{P}$ are projection matrices onto the orthogonal "signal-plus-noise" and "noise" subspaces, respectively.

IV. An SNR estimator derived from a basic channel estimation method

We have already seen that our SNR estimator is primarily based on the estimation of the channel coefficients and the detected symbols. But, generally speaking, one can state that we can always obtain SNR estimates form any channel estimator and detected symbols. However, it should be noted that SNR estimates that can be directly found using classical channel estimation techniques would not always be accurate. This is because these channel estimation techniques do not care about the accuracy of the noise power estimation as they are only geared towards the accurate detection of the transmitted data symbols. In this section, for the sake of briefness, we will introduce a basic channel estimation technique and show how it can be used to provide SNR estimates.

With the presence of pilot symbols, the most basic channel estimation technique is direct interpolation [10]. In fact, from the estimated channel coefficients at pilot positions, the channel parameters at other positions can be obtained by linear interpolation. Assuming flat fading conditions, the channel coefficients at pilot positions are simply estimated by dividing the received samples by the corresponding known pilot symbols, and one can therefore write

$$\hat{h}_i(n_p) = \frac{y_i(n_p)}{a(n_p)}, \quad n_p = 1, 2, \ldots, N_p, \tag{31}$$

where n_p are the time positions of the pilot symbols and N_p is the total number of these pilot symbols. Then, estimates of the channel parameters, $\hat{h}_i(n)$, of $h_i(n)$, at any time n, can be obtained by linear interpolation using the coefficients given in eq (31).

Now, once all the channel coefficients are found, the transmitted data symbols can be detected and can, thus, be used to find estimates of the SNR. In fact, an estimate of the signal power, $\hat{P}_i$, and the noise power $\hat{N} = 2\hat{\sigma}_i$, are obtained, respectively, using eqs. (32) and (33)

$$\begin{aligned} \hat{P}_i &= \frac{\sum_{n=1}^{N}|\hat{h}_i(n)\hat{a}(n)|^2}{N}, &(32)\\ \hat{N}_i &= \frac{\sum_{n=1}^{N}|y_i(n) - \hat{h}_i(n)\hat{a}(n)|^2}{N}, &(33)\end{aligned}$$

where $\hat{a}(n)$, $n = 1, 2, \cdots, N$, are the detected symbols. Estimates of the SNR are therefore obtained as

$$\hat{\rho}_i = \frac{\hat{P}_i}{\hat{N}_i} \tag{34}$$

V. Simulation results

We will now assess the performance of our new estimator via Monte Carlo simulations over 1000 realizations. The number of antenna branches will be set to $N_a = 8$. The DA method will refer to the case where all the transmitted symbols are supposed to be known to the receiver ($N_p = N$). Whereas the DD method will refer to the case where only a subset of the N_p transmitted symbols is ideally known to the receiver.

Fig. 1 shows the empirical NRMSE as a function of the true SNR under a Rayleigh time-varying fading channel for both

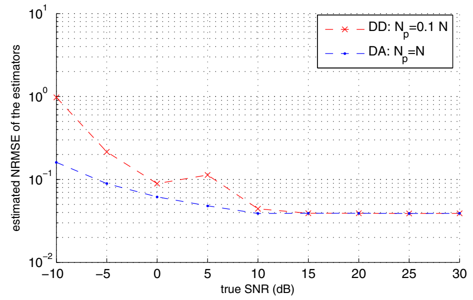

Fig. 1. SNR NRMSE on one of the 8 antenna elements, 16-QAM, $fs = 243$ kHz, $f_D = 100$ Hz, $L_c = 5$, $N = 1000$.

DA and DD scenarios. We notice that our LS-based method seems to perform well over the entire SNR range, more so over the practical medium range. Next, we will show that the estimation accuracy of our new LS-based method primarily depends on the size of the observation interval N.

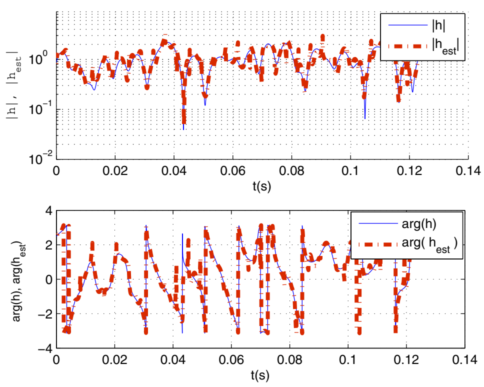

Fig. 2. Channel modulus and phase argument, and their estimates, on one of the 8 antenna elements, SNR = 10 dB, 16-QAM, $f_s = 243$ kHz, $f_d = 1000$ Hz, $L_c = 5$, $N = 100$, $N_p = 0.1N$.

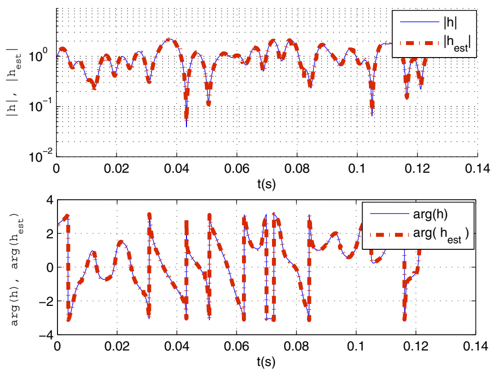

Fig. 3. Channel modulus and phase argument, and their estimates, on one of the 8 antenna elements, SNR = 25 dB, 16-QAM, $f_s = 243$ kHz, $f_d = 1000$ Hz, $L_c = 5$, $N = 100$, $N_p = 0.1N$.

Figs. 2 and 3 depict the estimation accuracy of the coefficients ($\boldsymbol{c}_i$) of the complex channel. The maximum Doppler frequency is set to $f_d = 1000$ Hz. Only 100 transmitted symbols are considered, at a time for the estimation which will be shown to be sufficient to estimate the signal power but not enough to precisely estimate the noise power σ^2.

In fact, from Figs 2 and 3, we see that the channel coefficients, for the considered high SNR values (10 dB and 25 dB), are estimated with relatively high accuracy. This results in accurate estimates for the matrices $\boldsymbol{C}$ and $\boldsymbol{A}$. Consequently, the signal power $P_i = \widehat{\boldsymbol{c}}_i^H \boldsymbol{T}^T \widehat{\boldsymbol{A}}^H \widehat{\boldsymbol{A}} \boldsymbol{T} \widehat{\boldsymbol{c}}_i$ is estimated quite accurately and the main cause for performance degradation, in the SNR estimation process, stems from the inaccurate estimation of the noise power, a behavior that is better illustrated in Fig 4.

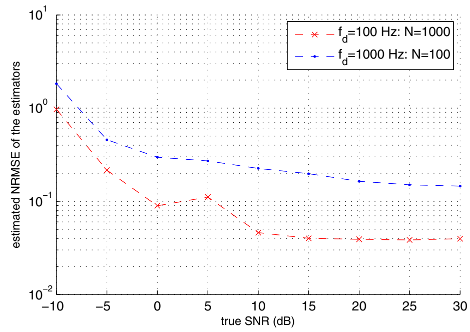

Fig. 4. SNR NRMSE on one of the 8 antenna elements for different Doppler frequencies, 16-QAM, $L_c = 5$, $f_s = 243$ kHz, $N_p = 0.1N$.

Indeed, Fig. 4 depicts the effect of varying the size of the observation interval N on the performance of our new estimator. It shows the NRMSE for the DD approach over a Rayleigh channel, when $f_d = 100$ Hz and $f_d = 1000$ Hz. In fact, the size of the estimation interval N can not be arbitrarily chosen. This is because we should always respect the condition $(\frac{f_d}{f_s})N \ll 1$ so that the channel can be accurately approximated by a polynomial in time. Indeed, for a constant sampling rate, the value of N depends on the value of the maximum Doppler frequency f_d.

From Fig. 4, a significant difference in performance is observed between the two curves. In fact, when $f_d = 1000$ Hz, to respect the condition $(\frac{f_d}{f_s})N \ll 1$, we have selected $N = 100$ symbols. Consequently, with such a relatively low value of N, the noise power σ^2 can not be very accurately estimated. However, a lower Doppler frequency ($f_d = 100$ Hz) allows us to increase the number of received symbols used in the estimation process to $N = 1000$ symbols. Thus, we obtain a more accurate local estimate of the noise power and consequently a more accurate estimate of the SNR. In fact, increasing the number of samples in the observation interval clearly increases the estimation accuracy over the entire SNR range. Finally, it should be noted that the optimal choice of N depends on the SNR value, as well as on the ratio $(\frac{f_d}{f_s})$.

Fig. 5, shows the estimated NRMSE, as a function of the true SNR values, for both our new LS-based SNR estimator and the SNR estimator that can be inferred from the basic channel estimation method, which will be simply referred to

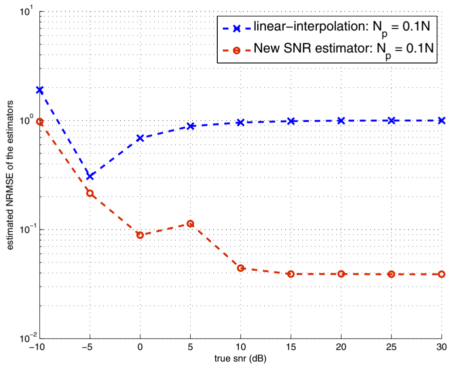

Fig. 5. SNR NRMSE on one of the 8 antenna elements, 16-QAM, $L_c = 5$, $f_s = 243$ kHz, $N_p = 0.1N$.

as the "linear interpolation" SNR estimator. We see that the "linear interpolation" estimator exhibits poor performances as compared to our new LS-based SNR estimation technique. In fact, the SNR estimates provided by the "linear interpolation" SNR estimation procedure are not accurate for the entire SNR range. Indeed, this method fails to estimate the SNR as it is based on a channel estimation technique that is, like most of the classic channel estimation method, mainly derived for the detection of the transmitted data symbols, without taking into account the noise power estimation accuracy. In fact, in the high SNR region, where the noise power is too small, the channel parameters can reasonably be estimated using eq. (31) since the very small noise components can be approximated to zero. Most of the transmitted data can consequently be correctly detected and, therefore, the signal power P_i can be accurately estimated, contrarily, to the noise power estimate $\hat{N}$ which is too noisy, leading to inaccurate SNR estimates. On the other hand, in the low SNR region, the noise power is relatively high. Consequently, the noise components should not be approximated by zero as done in eq. (31). This results in very inaccurate estimates of the channel coefficients in the pilot positions and, later on, in the non-pilot positions. Hence, the transmitted data are not accurately detected, which ultimately leads to inaccurate estimates of the SNR. In the medium SNR region, a tradeoff between the channel coefficients and the noise power estimation accuracy leads to more accurate estimates of the SNR, as it can be seen in Fig. 5.

In contrast, our LS-based SNR estimation method exhibits better performances over the entire SNR region. This is because the channel is locally approximated by a polynomial in time. Then, the signal and noise powers are estimated by orthogonal projection, respectively, onto the signal and noise subspaces thus providing more accurate SNR estimates.

VI. Conclusion

In this paper, the estimation of the instantaneous SNR, under time-varying flat fading SIMO channels, for QAM signals, was addressed. We developed a novel LS-based estimator. Polynomial fitting is used to locally approximate the channel. Our DD method bases the estimation process on the use of some pilot symbols. The new estimator was shown to have a satisfactory performance over the entire SNR range. Also, for a wide range of reasonably high SNR values, our DD method was shown to exhibit a performance similar to the one that could be achieved if all symbols were ideally known to the receiver.

We have also shown that our LS-based SNR estimator outperforms, as expected, an SNR estimator directly derived from a well known basic channel estimation technique.

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