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Subspace-Based SNR Estimator for Cognitive Radio and Link Adaptation

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ABSTRACT / *RESUMEN*

Signal-to-Noise Ratio (SNR) parameter represents the main metric to characterize the performance of signal reception. Determining this parameter is of major importance for a wide variety of communication techniques such as spectrum sensing in Cognitive Radio, Link Adaptation, and power allocation. In general, there are two kinds of SNR estimation techniques: Data-Aided (DA) and Blind Estimation (BE). By using Data-Aided estimation (DA), the receiver estimates the SNR based on prior information from the transmitter. On the other hand, by using Blind-Estimation (BE), the receiver does not have any prior-knowledge of transmission parameters. This technique is extremely used for scenarios where transmission parameters are unknown, a common situation on spectrum sensing for non-cooperative applications in Cognitive Radio. However, some reported BE algorithms have been developed exploiting specific properties of some modulation schemes, which also demands some prior knowledge of signal parameters. This work is focused on describing SNR estimation algorithms suitable for several digital and analog modulation schemes. We propose the Subspace-Based SNR estimator for spectrum sensing by using the Energy Detector and Link Adaptation applications. Comparative simulation results regarding estimator performance exhibit the high precision for several channel models. The applicability of this estimator for several analog and digital modulation schemes is also shown as well as proper performance for low SNR levels is obtained, in exchange for higher computational complexity.

Keywords: Signal-to-Noise Ratio Estimation; Blind Estimation; Cognitive Radio; Energy Detector; Link Adaptation.

Estimador de la SNR Basado en el Método del Subespacio para Radio Cognitiva y Adaptación de Enlace

RESUMEN

La Relación Señal a Ruido representa una de las principales métricas para caracterizar la recepción de una señal. Determinar con la mayor precisión posible este parámetro es de gran importancia para una variedad de técnicas de comunicaciones como: el sensado de espectro en la Radio Cognitiva, la Adaptación de Enlace y el control de potencia. En general, existen dos clasificaciones en cuanto a técnicas de estimación de la SNR: Las técnicas de estimación asistidas por datos (DA) y las técnicas de estimación a ciegas (BE). En la estimación asistida por datos (DA), el receptor estima la SNR basado en el conocimiento previo de los datos enviados por el transmisor. Por otra parte, en las técnicas de estimación a ciegas (BE), el receptor no conoce los parámetros de la transmisión de antemano. Esta técnica resulta de gran utilidad para escenarios donde se desconocen parámetros de la transmisión, situación típica del sensado de espectro en la Radio Cognitiva en escenarios no cooperativos. Sin embargo, algunos de los algoritmos BE han sido desarrollados aprovechando propiedades específicas de algunos esquemas de modulación, lo cual implica el conocimiento previo de los parámetros de la señal. Este trabajo está enfocado en la descripción de algoritmos de estimación de la SNR aplicables a varios esquemas de modulación digital y analógica. Se propone el algoritmo de estimación de la SNR basado en el método del subespacio para aplicaciones de sensado de espectro con el empleo del detector de energía y adaptación de enlace. Resultados comparativos por simulaciones en relación al desempeño del estimador muestran la precisión del mismo para varios modelos de canales. También se muestra la aplicabilidad de este estimador para varios esquemas de modulaciones analógicas y digitales, así como un buen desempeño del mismo en bajos niveles de SNR, a cambio de una mayor complejidad computacional.

Palabras claves: Estimación de la Relación Señal a Ruido; Estimación a Ciegas; Radio Cognitiva; Detector de Energía; Adaptación de Enlace.

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1. - INTRODUCTION

Link Adaptation technique improves the rate of transmission by exploiting the channel state information (CSI). This technique is highly used for mobile networks and Digital Video Broadcasting by satellite, where SNR parameter estimation results of major importance. The precision of spectrum sensing techniques in Cognitive Radio (CR) systems is constrained by the estimation of communication channel parameters, in which one of the main parameters is the Signal-to-Noise Ratio (SNR).

In this work, it is considered to carry out SNR parameter estimation from Radio Frequency (RF) signals for Cognitive Radio and Link Adaptation applications in case of non-cooperative communications. This is implemented to perform spectrum sensing operations, where signal detection represents the first task to be accomplished. In this regard, energy detection has been commonly adopted for spectrum sensing. This is due to its low computational complexity and does not require prior information from the signal to be detected. However, the precision of this technique is conditioned by the precision of the estimated noise power. In this study, it is considered a single carrier communication link with digital or analog modulation waveforms. In addition, interference is assumed to be Additive White Gaussian Noise (AWGN).

Most SNR estimators can be roughly categorized into two couples of classes, one is Data-Aided (DA) and Decision-Directed (DD) and the other is Blind-Estimator (BE) and Non-Data-Aided (NDA) methods[1] [1–4]. DA methods estimate the SNR parameter using the periodic reception of transmitted symbols by training sequences. These received symbols are usually used for channel estimation, where an approximated channel frequency response is obtained. Data-Aided estimation techniques are of widespread use due to their simplicity and effectiveness. However, they undermine power saving criteria and decrease the spectral efficiency of the system, especially when there is a fast variation of channel parameters over time [2, 3]. To avoid these limitations, other techniques have been developed, although the lack of effectiveness and the increase of computational complexity still represent open problems [1–5].

Decision-Directed estimators (DD) use demodulated symbols to estimate the SNR parameter. In this case, the use of training sequences from DA methods is avoided to improve the efficient use of spectrum capacities. However, feedback decisions may be affected by decision errors, especially in scenarios of low SNR levels. These methods could be considered as a special case of DA estimators, where training sequences are replaced by output symbols from the decoder [5]. In general, DD methods have acceptable performance for slow variation channels and lower noise levels. However, DA methods are more accurate in comparison with DD estimators, especially for low SNR levels [7, 8].

Non-Data-Aided (NDA) and Blind-Estimators (BE) methods estimate the SNR parameter without any prior knowledge of received data [9]. There are some reported NDA estimators, which operate, based on prior knowledge of some communication parameters. On the other hand, BE obviate prior knowledge of any parameter such as type and modulation index and channel characteristics. These methods exploit mathematical and/or statistical properties of transmitted signals in exchange of increasing complexity. The NDA solutions are also less accurate than DA estimators, especially for low SNR levels. The great advantage of BE algorithms is that they allow avoiding the spectral inefficiency of DA estimators and make the estimation without prior knowledge regarding communication parameters. This is why generally NDA and BE methods tend to be the slowest in terms of convergence and computationally more complex. Nevertheless, there is a group of (NDA) moments-based SNR estimators, which are computationally simpler although some communication parameters are assumed. These NDA solutions are not feasible to spectrum sensing scenarios with unknown parameters in Cognitive Radio [10, 11]. Recently in [12], [13] and [14] blind SNR estimation methods have been developed for any modulation scheme. These have the potential to be used in several applications such as spectrum sensing in Cognitive Radio and Link Adaptation. These blind estimators are sometimes reported as Non-Modulation-Aided estimators (NMA).

SNR estimation in Link Adaptation and spectrum sensing applications in non-cooperative scenarios demands for some requirements. On Link Adaptation applications, changes in the modulation scheme take place, and the estimator must maintain accuracy for any modulation scheme. Regarding spectrum sensing for Cognitive Radio, sometimes it is necessary to operate in low SNR levels. This is common on networks of a large number of users. In this case, an accurate estimator is required for low SNR levels. Based on non–cooperative communications, DA estimators, as well as DD solutions, are

[1] Some authors report classifying NDA algorithms into two subcategories: The I/Q estimators, which make use of the in-phase and quadrature components of the signal; and the envelope-based estimators (EVB), which only make use of the absolute value of the received complex signal to estimate the SNR.

discarded provided the need for prior knowledge regarding signal parameters. On the other hand, there are NDA algorithms based on prior knowledge of communication parameters for baseband signals, such as the Squared Signal-to-Noise Variance (SNV) [15] and the Signal-to-Variation Ratio (SVR) estimators [16]. However, these NDA estimators were generally developed for some specific digital modulation schemes and they are only suitable to those schemes and for baseband signals [17].

The main goal of this work is to describe a BE estimator for the SNR parameter, which could be applicable to Cognitive Radio and Link Adaptation. The applicability of this algorithm for spectrum sensing with Energy Detector on several communications channel models is discussed and also verified through simulations. Major contributions of this paper are summarized as follows:

- A detailed comparison regarding SNR estimation techniques for Cognitive Radio and Link Adaptation is discussed. This is a subject not fully addressed on reported papers.
- Representative channel models and modulation schemes for Cognitive Radio applications and Link Adaptation techniques are summarized from a variety of journal articles.
- Novel issues for the analyzed SNR estimation techniques regarding applicability on wireless scenarios are illustrated.
- Energy Detector scheme is evaluated by connecting the proposed noise estimation.

Remaining sections of this article are organized as follows: In Section 2 some reported SNR estimators and its applicability to Cognitive Radio and Link Adaptation is analyzed, in Section 3 a BE SNR estimator applicable to Cognitive Radio and Link Adaptation is described. In Section 4, the description of the Energy Detection by using the BE SNR estimator is addressed. In Section 5 the algorithm applicability for several modulation schemes, as well as the accuracy for Rayleigh and Rician channel models schemes is analyzed. Finally, Section 6 summarizes the main conclusions of this article.

2. - REPORTED NDA ESTIMATORS FOR PASSBAND SIGNALS

The great majority of reported estimators have been developed for specific modulation schemes for baseband signals. In this section, an analysis about the applicability of some reported algorithms for Cognitive Radio and Link Adadptación applications is addressed. Papers in [7, 16] report the Signal-to-Variation Ratio (SVR) estimator for M-ary PSK baseband signals in real and complex AWGN channels. Another method is described in [15] reported by the Squared Signal-to-Noise Variance (SNV) estimator and it is derived for M-ary PSK baseband signals also for real and complex AWGN channels. These estimators demand for handshaking signaling between transmitters and receivers as well as to demodulate the signal of interest in order to estimate the SNR parameter. In this regard, these methods are not affordable to non-cooperative scenarios in CR applications.

The second and fourth order moments $M_2\ M_4$ based SNR estimator described in [15] is a conventional NDA algorithm to estimate SNR for M-PSK, M-QAM, APSK, and FM waveforms. This algorithm was initially used to estimate the SNR parameter on baseband signals by the expression

$$\widehat{\mathrm{SNR}} = \frac{\sqrt{2M_2^2 - M_4}}{M_2 - \sqrt{2M_2^2 - M_4}}, \tag{1}$$

where M_2 and M_4 represent statistical moments of the received signal. Expression in (1) is derived considering that AWGN kurtosis (k_n) and baseband signals kurtosis (k_s) without noise are previously known. This algorithm can be used to carry out the SNR estimation of constant envelope RF signals where the typical value of signal kurtosis is k_s=1.5. It can be assumed from expression in (1) that this estimator is only applicable to AWGN channels provided this expression is obtained by assuming kurtosis value of the signal of interest, which represents an unknown parameter in fading channels. The algorithm is also applicable to non-constant envelope modulation schemes such as APSK and QAM. In these cases, it is required prior knowledge of the modulation order to obtain the kurtosis of the signal without noise by the expression: $k_s = 1 + 2/5[1 - 3/(M-1)]$, where M represents the modulation order. This algorithm could be applicable to Link Adaptation schemes for AWGN channels only. In case of spectrum sensing for non-cooperative scenarios, the M_2M_4 estimator is only applicable for signals of constant envelope.

The split-symbol moment estimator (SSME) is a reported NDA method to estimate the SNR parameter [5]. This method exploits the property that noise samples in a symbol interval are uncorrelated, while the signal without noise samples are correlated. This algorithm performs the SNR estimation based on prior knowledge of symbol intervals in a perfectly synchronized system. In addition, if the signal is affected by multipath fading, performance is highly deteriorated, due to the lack of correlation between samples of the signal of interest. Nevertheless, this algorithm exhibits proper performance at low SNR ranges. However, the SSME estimator is only used for some digital modulations such as: M-PSK, M-QAM, APSK and GMSK signals. The SNR estimation using the SSME algorithm is obtained through the following expression

$$\widehat{\mathrm{SNR}} = \frac{\frac{1}{N_m}\sum_{i=1}^{I}\sum_{k=1}^{N_s}\left|y_{i,k}\right|^2 - \frac{1}{N_m}\sum_{i=1}^{I}|R_i|^2}{\frac{1}{N_m}\sum_{i=1}^{I}|R_i|^2}, \tag{2}$$

where

$$R_i = \sum_{k=1}^{N_s/2}\left(y_{i,2k} - y_{i,2k-1}\right). \tag{3}$$

In the above expressions, N_s represents the total number of samples per symbol to process, N_m represents the total numbers of samples of the received signal. The quantity R_i in (3) brings noisy samples from the i-th symbol interval of the received signal $\mathbf{y}$. Expression in (2) is only applicable when samples of the signal of interest are highly correlated. SSME estimator could not be applied for spectrum sensing applications in Cognitive Radio due to assumptions of perfect synchronization. This algorithm could be used to estimate the SNR parameter on Link Adaptation applications, but only for AWGN channels and for some specific phase modulation schemes.

3. - BLIND SNR ESTIMATOR FOR DIGITAL AND ANALOG MODULATION WAVEFORMS

The Subspace-Based SNR estimator is a BE estimator for RF signals. This algorithm is based on the correlation matrix of the received signal. The Subspace-Based SNR estimator reported in [12] is applicable to AWGN, Rayleigh and Rician channels, and is well suited for any single carrier digital and analog modulation formats. Furthermore, this algorithm presents high accuracy at low SNR levels regarding other reported algorithms. These conditions allow the Subspace-Based SNR estimator to be applicable to Cognitive Radio and Link Adaptation scenarios.

Considering the received discrete-time signal $\mathbf{y}$ from AWGN channels, then the signal model is given by

$$\mathbf{y} = \mathbf{s} + \mathbf{n}, \tag{4}$$

where $\mathbf{s}$ represents the signal of interest and $\mathbf{n}$ is an independent zero-mean process from AWGN processes. The random variable $\mathbf{n}$ is a non-correlated process, analytically described by

$$\mathbf{n} \sim \mathcal{N}_{\mathbb{C}}(0, \sigma_n^2). \tag{5}$$

By using properties of (5), the autocorrelation matrix of $\mathbf{y}$ is obtained by

$$\mathbf{R}_{yy} = \mathbb{E}[\mathbf{y}\mathbf{y}^H] = \mathbb{E}[(\mathbf{s}+\mathbf{n})(\mathbf{s}+\mathbf{n})^H] = \mathbb{E}[\mathbf{s}\mathbf{s}^H] + \sigma_n^2\mathbf{I} = \mathbf{R}_{ss} + \sigma_n^2\mathbf{I}, \tag{6}$$

where $\mathbf{n}^H$ denotes the conjugate-transpose of $\mathbf{n}$ and $\mathbf{n}^T$ denotes the transpose of $\mathbf{n}$, σ_n^2 is the noise power, $\mathbf{I}$ represents the identity matrix. $\mathbf{y} = [y_1, y_2, \ldots, y_{N_m}]^T$ is the received signal, $\mathbf{s} = [s_1, s_2, \ldots, s_{N_m}]^T$ represents the signal of interest, $\mathbf{n} = [n_1, n_2, \ldots, n_{N_m}]^T$ represents noise, $\mathbf{R}_{ss} = \mathbb{E}[\mathbf{s}\mathbf{s}^H]$ is the autocorrelation matrix of the signal of interest without noise and L

is the matrix order. Based on properties of autocorrelation matrices of the RF signal [18], $\mathbf{R}_{ss}$ is a positive semi-definite matrix of rank $(q < L)$. In this case, the $L - q$ smaller eigenvalues λ_i $(q < i < L)$ that result from the matrix decomposition of $\mathbf{R}_{ss}$ are approximately zero. Considering the matrix property that the trace is equal to the sum of the eigenvalues, by sorting the eigenvalues from the matrix decomposition of $\mathbf{R}_{yy}$ in (6) as $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_L$, then the mean of the smaller $(L - q)$ eigenvalues of $\mathbf{R}_{yy}$ are approximately the noise power (σ_n^2), this is denoted by

$$\widehat{\sigma_n^2} = \frac{1}{L-q}\sum_{i=q+1}^{L} \lambda_i, \tag{7}$$

where $\widehat{\sigma_n^2}$ is an approximation σ_n^2. Denoting the signal power without noise by σ_s^2, then this parameter may be obtained by

$$\widehat{\sigma_s^2} = \left(\frac{1}{N_m}\sum_{k=1}^{N_m} |y_k|^2\right) - \widehat{\sigma_n^2}, \tag{8}$$

where N_m is the total number of samples of the received signal. By using expression above the SNR parameter can be estimated by

$$\widehat{\mathrm{SNR}} = \widehat{\sigma_s^2} \Big/ \widehat{\sigma_n^2}. \tag{9}$$

On the formulation above, to determine the subspace q represents the major problem of this method. To determine this subspace, the Minimum Description Length principle (MDL) is used [19]. MDL principle allows detecting the total number of most representative values of data strings. Assuming the received signal of N_m samples is divided into time slots of L samples, then there are $N = N_m/L$ vectors of L components. Thus, after obtaining the eigenvalues the following expression corresponding to MDL principle is used

$$\mathrm{MDL}(k) = -\log\left(\frac{\prod_{i=k+1}^{L} \lambda_i^{\frac{1}{L-k}}}{\frac{1}{L-k}\sum_{i=k+1}^{L} \lambda_i}\right)^{(L-k)N} + 0.5k(2L-k)\log(N). \tag{10}$$

The subspace of signal with noise q corresponds to the value of k that minimizes the previous expression by

$$q = \arg\min_{k} \mathrm{MDL}(k). \tag{11}$$

In order to summarize, the described method above can be applied by the following steps to estimate the SNR parameter:

1. Determine the autocorrelation matrix $\mathbf{R}_{yy}$ of the received signal by the expression in (6).
2. Compute eigenvalues of the matrix $\mathbf{R}_{yy}$ by numerical algorithms such as QR Algorithm or Power Method [20].
3. Compute the rank of matrix $\mathbf{R}_{ss}$ using the MDL principle in (11).
4. Estimate noise power by expression in (7).
5. Compute signal power by expression in (8) and compute the estimated SNR according to (9).

The algorithm described above can be applied to several schemes of digital and analog modulations, thus it is suitable for Link Adaptation scenarios and CR applications.

4. - ENERGY DETECTOR IMPLEMENTATION BY USING THE SUBSPACE-BASED SNR ESTIMATOR

Signal detection represents the first task to be accomplished in Cognitive Radio. Consequently, several spectrum sensing techniques have been developed such as: Cyclostationary Detector [21], Matched Filter [22], Energy Detector [23], Wavelets [24] and Eigenvalue [25]. Performance of spectrum sensing techniques is closely related to the process related to sampling signals and processing [26]. From the perspective of signal detection, there are two categories in which different reported techniques can be grouped to determine whether the channel is available. These categories are: coherent detection and non-coherent detection [27]. The former includes all those methods in which the signal of interest is detected when compared with a locally generated signal. This demands prior knowledge regarding the parameters used to modulate the transmitted signal, such as frequency of the carrier and the used modulation order. Non-coherent techniques for spectrum measurement are those that do not require prior knowledge regarding the parameters of the signals of interest. These techniques are used in non-cooperative scenarios in Cognitive Radio. When noise variance value is available, the simplest method to perform spectrum sensing is given by the Energy Detector. This technique has been the most studied for measuring the spectrum, and its performance has been evaluated under multiple conditions of the communication channel. However, precision of this method is highly conditioned by the accuracy of the noise variance estimation. This section discusses Energy Detector scheme by using the Subspace-Based SNR estimator.

Figure 1 introduces the block diagram to connect the noise estimation method (Estimator Block) and energy measurement blocks (Energy Detector). Detection threshold value (λ) can be determined according to the Neyman-Pearson rule by using the maximum likelihood test [27].

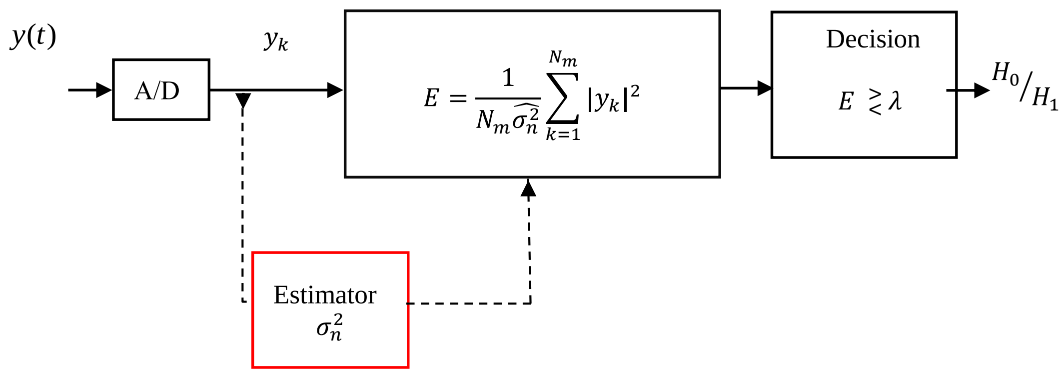

Figure 1
Block diagram of Energy Detector.

The detection probability (P_d) and the false alarm probability (P_f), both values to assess spectrum sensing performance of the Energy Detector, can be evaluated by [27]

$$P_f = Q\left(\frac{\lambda - N_m}{\sqrt{2N_m}}\right), \tag{12}$$

$$P_d = Q\left(\frac{\lambda - N_m(1 + \mathrm{SNR})}{\sqrt{2N_m(1 + \mathrm{SNR})}}\right), \tag{13}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{\frac{-t^2}{2}}\,dt$ and λ is the decision threshold. From (13) the decision threshold is established in terms of P_f and N_m by

$$\lambda = N_m + \sqrt{2N_m}Q^{-1}(P_f). \tag{14}$$

By using the decision threshold value from (15), the probability of detection (P_d) considering the Subspace-Based SNR estimator will be

$$P_d = Q\left(\frac{\lambda - N_m\left(1+\widehat{\mathrm{SNR}}\right)}{\sqrt{2N_m\left(1+\widehat{\mathrm{SNR}}\right)}}\right). \tag{15}$$

5. - RESULTS AND DISCUSSION

Simulations to validate the Subspace-Based SNR estimator performance and its applicability for Link Adaptation and Cognitive Radio are presented by using the mathematical software tool MATLAB. A Monte Carlo simulation of 500 attempts has been performed due to the randomness of the signals. In addition, comparative results are shown with the other two mentioned SNR estimators for RF signals in Section 2. Signals to simulate have been created with random parameters such as bit rate and modulation scheme. The carrier frequency is settled by $f_c = 400$ MHz. Parameters that characterize Rician and Rayleigh channel models have also been considered as follows: Rician distribution having $K = 3$, Doppler shift is taken to be in the range 50Hz to 100 Hz and path delay has been chosen in the range between 20 μs and 80 μs. Performance is analyzed by the normalized mean square error (NMSE) criterion defined by $\mathrm{NMSE}\left(\widehat{\mathrm{SNR}}\right) = \mathbb{E}\left[\left(\widehat{\mathrm{SNR}} - \mathrm{SNR}\right)^2\right]/\mathrm{SNR}^2$, where SNR is the true SNR value and $\widehat{\mathrm{SNR}}$ is an estimated value. This metric is commonly used to measure estimator quality. Provided that useful applications of SNR estimator are ranged on values below 0.5 for the NMSE metric, the analysis that follows exhibits results limited on the range [0, 0.5]. Considering NMSE metric versus SNR parameter the estimator is really "blind" to any considered modulation. To evaluate the performance of the Energy Detector for $N_m = 1024$ samples, the detection probability P_d vs SNR is considered. Computational complexity of algorithms is also evaluated by considering the total number of required operations to their implementation.

Figure 2 shows the performance of the Subspace-Based SNR estimator for different modulation schemes. The mean value provided by the proposed estimator is very close to the true SNR value to all exhibited modulation schemes. The figure also shows the normalized mean square error (NMSE) of the estimation. Values of NMSE are quite small and similar for all digital modulation schemes. This result introduces the applicability of the Subspace-Based SNR estimator for Link Adaptation applications.

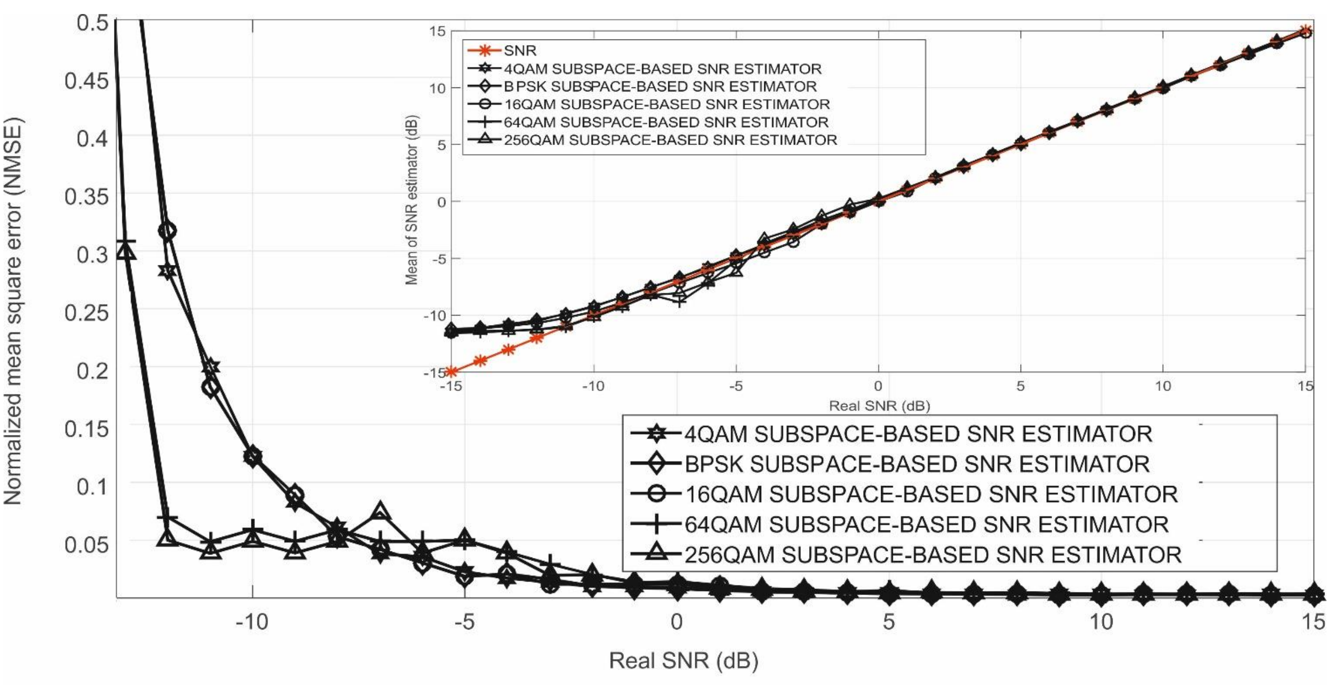

Figure 2
Mean value and normalized mean square error of estimation made by the Subspace-Based SNR estimator for several signals.

Figure 3 illustrates a comparison of the Subspace-Based SNR estimator to other two conventional algorithms (M_2 M_4 and SSME estimators) regarding NMSE and the mean of the estimated SNR. Figure 3 shows that mean value provided by the Subspace-Based SNR estimator is closer to the true SNR value than other two mentioned algorithms. This figure also shows that the values of the NMSE presented by Subspace-Based SNR estimator are lower than the error provided by other algorithms.

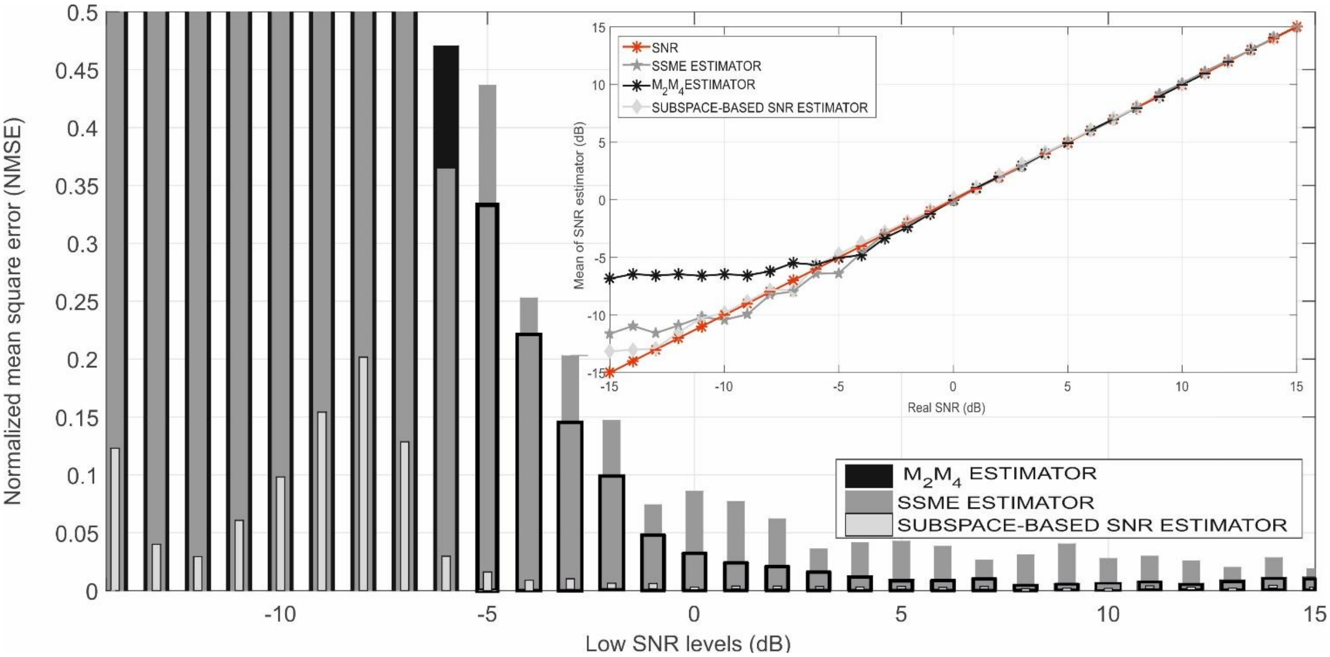

Figure 3
Mean value and normalized mean square error of estimation made by several estimators for QPSK signal in AWGN channel.

Figures 4 and 5 show results of the Subspace-Based SNR estimator in case of Rayleigh and Rician channel models. Figure 4 shows results by the Subspace-Based SNR estimator for Rayleigh channels. Additionally, Figure 4 shows the mean value of the SNR estimated values. The estimated parameter is nearly similar to the true SNR value and with the low error values of the NMSE. This has a similar behavior to results obtained for AWGN channel in Figure 3.

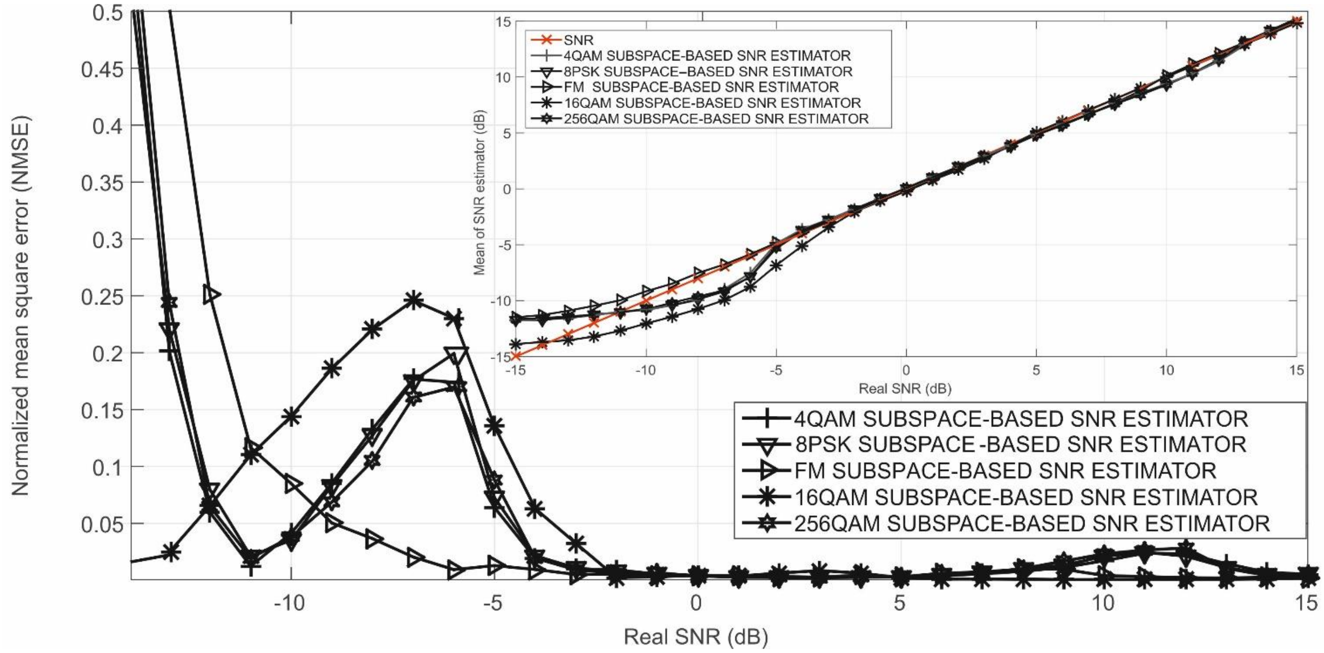

Figure 4
Mean value and normalized mean square error of estimation made by Subspace-Based SNR estimator for several signals in Rayleigh channels.

Figure 5 shows the estimated SNR value by the Subspace-Based SNR estimator for Rician channels. The figure shows the similarities between the estimation provided by this method and the true SNR value. When SNR is higher than -5 dB, NMSE values are quite small. This represents a similar behavior to the results obtained for a Rayleigh channel.

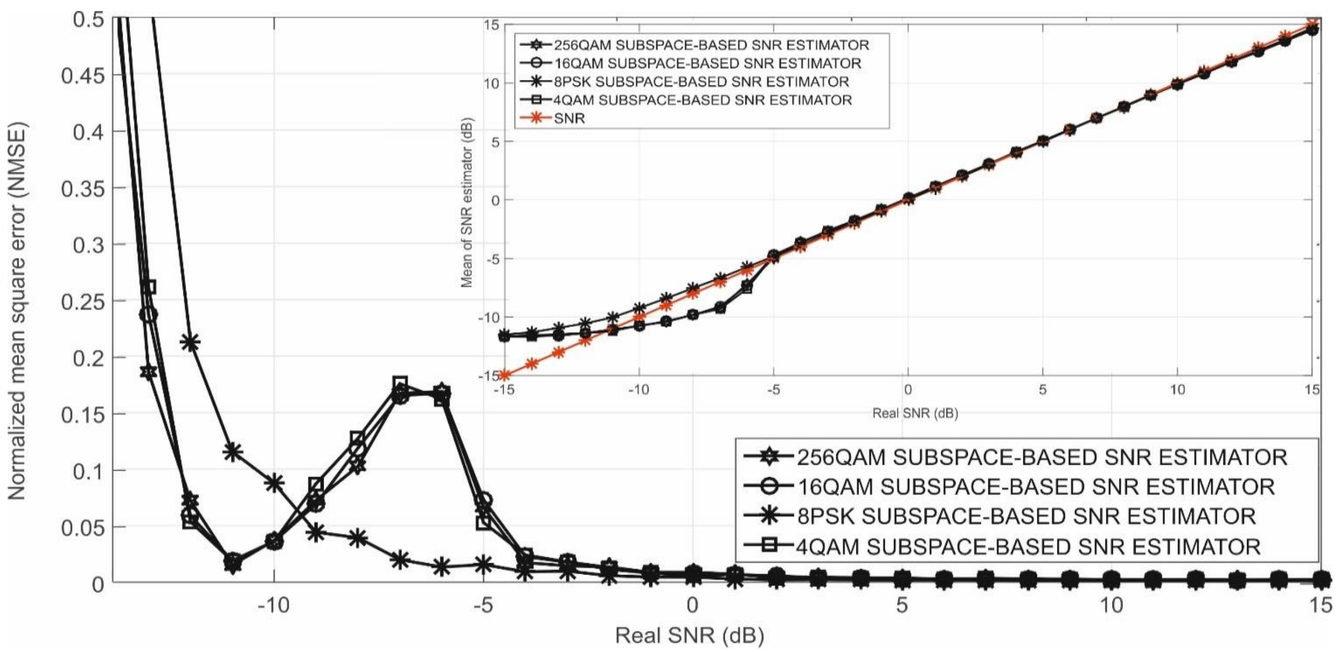

Figure 5
Mean value and normalized mean square error of estimation made by Subspace-Based SNR estimator for several signals in Rician channels.

Figure 6 shows the performance of the Energy Detector by using the blind SNR estimator. A variety of channel models are considered by transmitting digital modulation waveforms. Performance obtained by using the Subspace-Based SNR estimator is very close to the ideal P_d from ED method when SNR is higher than -5 dB.

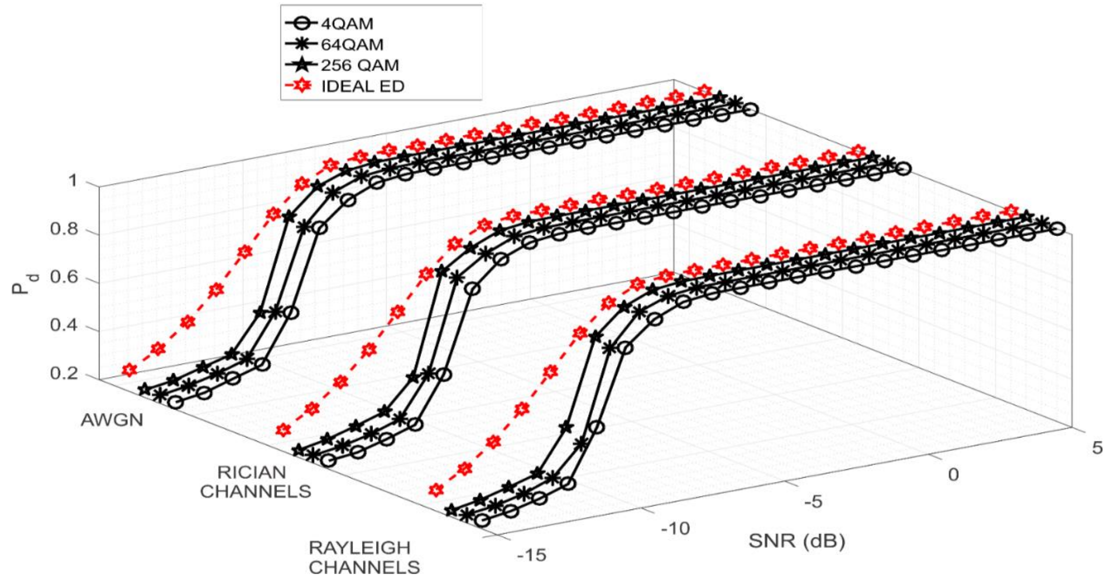

Figure 6

Detection probability P_d vs $\mathrm{SNR(dB)}$ with $P_f = 0.1$ for signals with digital modulation in different channel models.

The Subspace-Based SNR algorithm can be applied to several schemes of digital and analog modulations for low SNR values. We are considering conventional digital modulations schemes from High-Speed Downlink Packet Access (HSDPA) technique and DVB-S2 standards to validate the SNR estimator applicability in these scenarios. These real-life scenarios commonly implement Link Adaptation techniques. The Subspace-Based SNR algorithm is also applicable to Rayleigh and Rician channel models. These are representative channel models of Digital Terrestrial Television (DTV), a possible spectral band to deploy Cognitive Radio techniques, considering the development of the IEEE 802.22 standard using TV white spaces.

To analyze complexity, Table 1 shows the total number of adders and multipliers to implement each considered method. This represents the common reported metric of complexity [2, 5, 14]. This table shows that the total number of multipliers and adders to apply Subspace-Based SNR estimator depends cubically on the total number of analyzed samples, while other algorithms exhibit a linear dependence. Subspace-Based SNR estimator is the most complex method due to matrix operations such as autocorrelation matrix decomposition. However, this method reports high accuracy levels for any considered signal and thus represents a useful application on blind estimation.

Table 1
Complexity of NDA SNR Estimation Techniques

Estimator	Adds	Multiplications
M_2M_4 Estimator	$4N_m - 2$	$5N_m + 1$
Split-Symbol Moment Estimation (SSME)	$4N_m + 1$	$N_m + 2$
Subspace-Based SNR Estimator	$8/3L^3 + \mathcal{O}(N_m^3)$	$8/3L^3 + \mathcal{O}(N_m^2)$

6. - CONCLUSIONS

Spectrum sensing operations for Cognitive Radio and Link Adaptation applications demand SNR parameter estimation. The second and fourth order moments M_2M_4 based SNR estimator can provide a "blind" SNR estimation in digital modulations scheme of constant envelope in AWGN channel. Although accuracy for low SNR levels is extremely degraded.

On the other hand, SSME estimator provides the accuracy that $M_2\ M_4$ estimator does not present for lower SNR levels. However, this algorithm is only applicable when the symbol rate and modulation scheme are provided, strong constraints in scenarios of blind spectrum sensing for Cognitive Radio applications.

In this work, we have proposed the application of the Subspace-Based SNR estimator to estimate the SNR parameter for Cognitive Radio applications in non-cooperative scenarios and Link Adaptation. Although the Subspace-Based SNR estimator presents the higher computational complexity, this method exhibits to have the best performance at low SNR values in comparison to other reported. In addition, this method does not require prior knowledge of the analog or digital modulation format. The Subspace-Based SNR estimator is also applicable to Rayleigh and Rician channel models with proper results in the range of SNR values of -5 dB to 15 dB.

Future work will be conducted by studying blind SNR estimation techniques applicable to Orthogonal-Frequency-Division-Multiplexing (OFDM) scheme. Additionally, to analyze the implementation of these solutions on hardware on FPGA devices may contribute to the further development of CR applications.

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