Set-Membership Adaptive Soft Combining for Distributed Cooperative Spectrum Sensing

Iker Sobron[†*], Wallace A. Martins[*], Francisco C. Ribeiro Jr.[*], Marcello L. R. de Campos[*]
[*]Federal University of Rio de Janeiro (UFRJ)
[†]University of the Basque Country (UPV/EHU)

***Abstract*—This paper presents a new adaptive soft combiner implemented on cognitive radio nodes for distributed cooperative spectrum sensing. The key feature of the proposal is the use of the standard set-membership normalized least-mean squares (SM-NLMS) algorithm, which enjoys good tracking capabilities, while entailing low computational burden. Indeed, simulation results show that the computational savings can be as high as 37% for 8 cooperating secondary users, as compared to another previously proposed data-selective soft combiner from the literature.**

I. Introduction

Cognitive radio (CR) has emerged as a promising technique to deal with the current inefficient usage of limited spectra [1], [2]. In the CR context, users who have no spectrum licenses, also known as secondary users (SUs), are allowed to take advantage of temporarily unused licensed spectrum [3]. In order to do that, SUs must *sense* which portions of the wireless spectrum are available, select suitable channels for their transmissions, manage the spectrum access with other SUs, and free those channels as long as primary users (PUs) "request" so. Within this process, the first step, referred as *spectrum sensing* (SS), is crucial for the proper functioning of a CR system.

The performance of SS techniques implemented by a single CR node is highly limited by local channel impairments. It is well-known that the most efficient way to improve such performance is to rely on *cooperative spectrum sensing* among nodes [4], [5], [6]. Indeed, due to the (likely) independent statistical channel behavior measured across different node locations, one can increase the chances of correctly detecting vacancies (also known as white spaces) in the spectrum. Cooperation increases the reliability of detection by the diversity among SUs, besides transferring part of the detection computations to other secondary nodes or a fusion center (FC) with higher computational capacity, thus forming a distributed or centralized network, respectively [3], [7].

There are many different approaches to tackle the cooperative spectrum sensing problem [3], [7]. From a practical point of view, the most attractive soft-combining techniques are those based on the linear combining of the estimates from distinct SUs in order to decide whether there are white spaces in the spectrum or not. Indeed, such an approach gathers the computational simplicity of linear combiners—a very desirable feature when dealing with power-constrained CR nodes—with incoherent energy detection—thus disregarding any coherence assumptions among PUs and SUs, another desirable feature in practice.

In the context of linear combining for SS, an optimal solution which maximizes the probability of detection (P_d) of a PU channel occupancy for a pre-defined probability of false alarm (P_f) was presented in [8]. The authors in [9] proposed an adaptive filtering solution using the least-mean squares (LMS) algorithm based on hard and soft combiners. Based on this work, a selective-updating version of the LMS soft-combiner which enables significant reduction of number of operations was proposed in [10]. The aim of this work is to go one step further by reducing even more the computational burden of the soft combiner through the use of a standard set-membership filtering (SMF) solution, namely the set-membership normalized LMS (SM-NLMS) algorithm.

A. Organization

The remainder of the paper is organized as follows: Section II presents the system model and the motivation for the use of an SMF solution for the described scenario. Section III makes a review of the SM-NLMS algorithm and Section IV presents a time-varying threshold for the error signal associated with the adopted adaptive filter. The performance of the proposed solution is assessed numerically in Section V and, finally, the main concluding remarks are drawn in Section VI.

B. Notation

Vectors and matrices are represented in boldface lowercase and uppercase letters, respectively. The operator $\text{Var}[\cdot]$ denotes the variance of a given random variable and $[\cdot]^T$ stands for usual transpose operator. Operators $|\cdot|$ and $\|\cdot\|$ correspond to the absolute value and norm-2, respectively.

II. System Model & Proposal

Following the system model of [8], we consider a cognitive radio network formed by secondary users spatially distributed. Each SU employs an energy detector to sense the environment under the hypotheses H_0 (absence of PU signal) and H_1 (presence of PU signal), such that the received signal at the mth SU can be formulated as follows:

$$x_m(n) = \begin{cases} v_m(n) & \text{if } H_0 \text{ holds} \\ v_m(n) + h_m s(n) & \text{if } H_1 \text{ holds} \end{cases}, \quad (1)$$

where the PU signal at discrete-time instant n has been represented as $s(n)$, being affected by a channel gain h_m and corrupted by a local zero-mean additive white Gaussian noise (AWGN) $v_m(n)$ with variance σ_m^2. It is assumed that the channel gain h_m is constant during the period of detection of spectrum vacancies.

Given a spatially anchored node with a pre-defined neighborhood, let us assume that its mth neighboring node generates a local energy estimate with N received samples as

$$y_m(k) = \sum_{n=0}^{N-1} |x_m(n+kN)|^2 , \quad (2)$$

which is then sent to the first mentioned node to be linearly combined. As it is shown in [8], for each fixed k, $y_m(k)$ follows a Chi-squared distribution of degree N, which can be approximated to a normal distribution with mean $\mu_m(k)$ and variance Var$[y_m(k)]$ for N large enough. As a result, $\mu_m(k)$ can be written as

$$\mu_m(k) = \begin{cases} N\sigma_m^2 & \text{if } H_0 \text{ holds} \\ [N+\eta_m(k)]\,\sigma_m^2 & \text{if } H_1 \text{ holds} \end{cases}, \quad (3)$$

where $\eta_m(k)$ is defined as N times the signal-to-noise ratio (SNR) at the mth neighboring node, i.e,

$$\eta_m(k) = \frac{|h_m|^2}{\sigma_m^2} \sum_{n=0}^{N-1} |s_m(n+kN)|^2 . \quad (4)$$

The variance is given as

$$\text{Var}[y_m(k)] = \begin{cases} 2N\sigma_m^4 & \text{if } H_0 \text{ holds} \\ 2\,[N+2\eta_m(k)]\,\sigma_m^4 & \text{if } H_1 \text{ holds} \end{cases}. \quad (5)$$

Thus, let the output of the soft combiner $y(k)$ be defined as

$$y(k) = \sum_{m=1}^{M} w_m(k)\, y_m(k) = \mathbf{w}^T(k)\,\mathbf{y}(k) , \quad (6)$$

where M is the number of neighbors of the node (including itself), $\mathbf{w}(k) = [w_1(k) \;\; w_2(k) \;\; \cdots \;\; w_M(k)]^T$ is the parameter vector of the linear soft combiner, and $\mathbf{y}(k) = [y_1(k) \;\; y_2(k) \;\; \cdots \;\; y_M(k)]^T$ denotes the vector containing the energy estimates of all of these M nodes. It is worth noting that a linear combination of normal distributions is a normal distribution, therefore, $y(k)$ is also a normally distributed variable weighed by the coefficients of $\mathbf{w}(k)$. At this stage, we wish to minimize the distance between the output of the linear combiner and a reference signal, constructed as

$$r(k) = \begin{cases} \mathbf{1}^T\boldsymbol{\mu}_0(k) & \text{if } H_0 \text{ holds} \\ \mathbf{1}^T\boldsymbol{\mu}_1(k) & \text{if } H_1 \text{ holds} \end{cases},$$

where $\mathbf{1}$ is a column vector with all elements equal to 1, $\boldsymbol{\mu}_0(k)$ denotes the column vector with the mean values $\mu_m(k)$ of the M local energy estimates, $y_m(k)$, under hypothesis H_0, whereas $\boldsymbol{\mu}_1(k)$ is the equivalent under hypothesis H_1. Although the ideal reference signal may not be available, a rather conservative estimate, $\hat{r}(k)$, was used in [10], [9]. The proposed adaptive filter structure is depicted in Fig. 1, in which the time-dependency on k is omitted for the sake of simplicity. Using a conservative rule for generating the estimate $\hat{r}(k)$ seems appropriate for the application at hand, for this implies that if any node senses the presence of a PU, the reference should indicate hypothesis H_1, even though it may increase probability of false alarm. However, we concede that more elaborate voting schemes may render better adaptive detection performance.

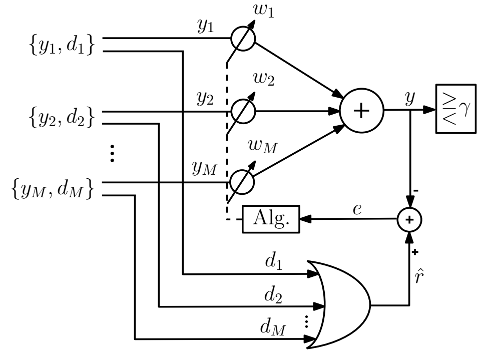

Fig. 1. Proposed adaptive linear combiner.

For instance, according to [10], [9], the local decisions just obtained could be once again shared within the neighborhood for a consensus decision in a two-step cooperation scheme. Although in [10], [9] the same neighborhood was used in both steps with good results, performance can be significantly improved if complementary neighborhoods are used for the first and second steps [11]. In any case, it is natural that good performance depends upon fast, reliable, and resilient behavior of the adaptive linear combiner.

Last step of the algorithm performs a detection test over a pre-computed local threshold $\gamma(k)$ that guarantees a pre-defined probability of false alarm P_f, which is supposed to be small, as follows:

$$y(k) \underset{H_0}{\overset{H_1}{\gtrless}} \gamma(k) . \quad (7)$$

At the same time as the coefficients of $\mathbf{w}(k)$ are updated in the adaptive filtering algorithm, we also refresh the decision threshold $\gamma(k)$ for the desired probability of false alarm P_f at each SU node as it is described below:

$$\gamma(k) = \boldsymbol{\mu}_0^T(k)\mathbf{w}(k) + Q^{-1}(P_f)\sqrt{\mathbf{w}^T(k)\,\boldsymbol{\Sigma}_{H_0}(k)\mathbf{w}(k)}, \quad (8)$$

where $\boldsymbol{\Sigma}_{H_0}(k)$ is a diagonal matrix with the variances Var$[y_m(k)]$ for $m = 1, \ldots, M$ with hypothesis H_0.

So far, we have presented the system model in a general manner, which implies that any adaptive filtering algorithm can be used in order to compute the weights of the soft combiner as it is shown in Fig. 1. In fact, an LMS and a selective-update version of the LMS have been proposed in [9] and [10] for updating the parameter vector of the soft combiner, respectively. The purpose of this work is to investigate the use of the standard SM-NLMS algorithm in the structure of Fig. 1 for adaptive computing of $\mathbf{w}(k)$. Such a goal is achieved by employing a variable error-bound, instead of the usually constant error bound imposed on standard SM-NLMS implementations [12]. Further details about the SM-NLMS algorithm are presented in the following section.

III. SM-NLMS: A Review

SMF is a general framework that allows one to deal with uncertainties of measured quantities commonly found in practice. Roughly speaking, the main idea underlying SMF is giving up the attempt to determine *the optimal parameters* associated with the related model (usually, a linear-in-parameter model); rather, SMF concept relates to finding *an optimal region* from which those parameters could be (heuristically, but automatically) chosen. Such an approach turns out to be very effective in practical contexts in which noise plays a major role. As a matter of fact, the reference signal $\hat{r}(k)$ described in the previous section might be very noisy, so that it might not be beneficial finding the optimal value for the parameter vector that best fits a sequence of such noisy reference.

Mathematically, given a tolerance $\bar{\gamma} \in \mathbb{R}_+$ associated with the error $e = r - y$ between a reference signal r and the output of the adaptive filter, we define the kth *constraint set* as

$$\mathcal{H}(k) = \{\mathbf{w} \in \mathbb{R}^M : |r(k) - \mathbf{w}^T\mathbf{y}(k)| \leq \bar{\gamma}\}, \tag{9}$$

in which k denotes a time-instant or iteration of the adaptive-filtering algorithm.

As mentioned before, instead of directly defining a cost function to be minimized, the SMF approach states that any vector $\mathbf{w}$ that satisfies

$$\mathbf{w} \in \bigcap_{k\in\mathbb{N}} \mathcal{H}(k) \tag{10}$$

is a feasible solution. The set of all such vectors $\mathbf{w}$ is called *feasibility set*. In online applications, we do not have access to all pairs $(r(k), \mathbf{y}(k))$ beforehand in order to compute the feasibility set, thus calling for approximate solutions.

The SM-NLMS algorithm [12] is an SMF-inspired adaptive technique that searches for an approximate feasible solution by iteratively enforcing that the parameter vector at the $(k+1)$th time-instant, $\mathbf{w}(k+1)$, is within $\mathcal{H}(k)$. In this case, if the current known parameter vector $\mathbf{w}(k)$ is already in $\mathcal{H}(k)$, then nothing has to be done, so that one can simply set $\mathbf{w}(k+1) = \mathbf{w}(k)$. However, if $\mathbf{w}(k) \notin \mathcal{H}(k)$, then one should find a vector $\mathbf{w}(k+1)$ such that $|r(k) - \mathbf{w}^T(k+1)\mathbf{y}(k)| \leq \bar{\gamma}$.

Note that, this search for an updated parameter vector $\mathbf{w}(k+1)$ should be performed in such a way that, ideally speaking, the newly found $\mathbf{w}(k+1)$ would also be within the previous constraint sets $\mathcal{H}(k-1), \mathcal{H}(k-2), \cdots, \mathcal{H}(0)$. Indeed, if this ideal condition holds, then

$$\left[\lim_{k\longrightarrow\infty} \mathbf{w}(k)\right] \in \bigcap_{k\in\mathbb{N}} \mathcal{H}(k), \tag{11}$$

thus implying that, in practice, $\mathbf{w}(k)$ would converge to a point in the feasibility set after a sufficiently large number of iterations.

A possible way of satisfying the above ideal condition is to find minimum disturbance solutions for the updated parameter vector $\mathbf{w}(k+1)$ which are in $\mathcal{H}(k)$. By minimum disturbance solutions we mean those that minimize $\|\mathbf{w}(k+1) - \mathbf{w}(k)\|$. Intuitively, this minimum disturbance is such that $\mathbf{w}(k+1) \approx \mathbf{w}(k)$, so that the chances are that $\mathbf{w}(k+1) \in \mathcal{H}(k-1)$, and so forth. Furthermore, since $\text{sign}[r(k) - \mathbf{w}^T(k+1)\mathbf{y}(k)]$ is likely to be equal to $\text{sign}[r(k) - \mathbf{w}^T(k)\mathbf{y}(k)] = \text{sign}[e(k)]$, then one has

$$\mathcal{H}(k) \approx \{\mathbf{w} \in \mathbb{R}^M : r(k) - \mathbf{w}^T\mathbf{y}(k) \leq \bar{\gamma}\,\text{sign}[e(k)]\}, \tag{12}$$

where operator $\text{sign}[\cdot]$ gives the sign of the input argument.

By taking all of these facts into account, an SM-NLMS updating recursion is defined by the solution of the following optimization problem: the filter coefficients update with minimal disturbance whenever $\mathbf{w}(k) \notin \mathcal{H}(k)$, where, in this case, we should solve

$$\min \|\mathbf{w}(k+1) - \mathbf{w}(k)\|^2 \tag{13}$$

$$\text{subject to:} \quad r(k) - \mathbf{w}^T(k+1)\mathbf{y}(k) = \bar{\gamma}\,\text{sign}[e(k)], \tag{14}$$

whose solution is given as

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \delta(k)\frac{\mathbf{y}(k)e(k)}{\mathbf{y}^T(k)\mathbf{y}(k)}, \tag{15}$$

in which

$$\delta(k) = \begin{cases} 1 - \frac{\bar{\gamma}}{|e(k)|}, & \mathbf{w}(k) \notin \mathcal{H}(k), \\ 0, & \mathbf{w}(k) \in \mathcal{H}(k). \end{cases}$$

IV. Time-Varying Error Threshold

It is important to note that SMF performance depends directly upon the tolerance $\bar{\gamma}$ chosen for the output error e. Most SMF applications consider a fixed pre-defined bound associated with the variance of the input observation noise. However, this strategy is not adequate for time-varying environments (e.g. those found in spectrum sensing applications) in which optimal bounds may also vary with time. In such cases, it is desirable to employ alternative solutions that dynamically update $\bar{\gamma}$ in accordance with variations in the channel [13].

For the system model introduced in Section II, another motivation for using a time-varying error bound is that we can calculate it directly as a function of the disturbance ν at output of the filter of Fig. 1, which is modeled, after convergence, as

$$\nu = r - \mathbf{w}_\text{o}^T\mathbf{y}, \tag{16}$$

where $\mathbf{w}_\text{o}$ is the Wiener solution. Indeed, consider the following expressions for the mean μ_ν and the variance σ_ν^2 of the disturbance:

$$\mu_\nu = \pi_0\left((\mathbf{1} - \mathbf{w}_\text{o})^T\boldsymbol{\mu}_0\right) + \pi_1\left((\mathbf{1} - \mathbf{w}_\text{o})^T\boldsymbol{\mu}_1\right), \tag{17}$$

$$\sigma_\nu^2 = \pi_0\left[\left((\mathbf{1} - \mathbf{w}_\text{o})^T\boldsymbol{\mu}_0 - \mu_\nu\right)^2 + \mathbf{w}_\text{o}^T\boldsymbol{\Sigma}_{H_0}\mathbf{w}_\text{o}\right] + \pi_1\left[\left((\mathbf{1} - \mathbf{w}_\text{o})^T\boldsymbol{\mu}_1 - \mu_\nu\right)^2 + \mathbf{w}_\text{o}^T\boldsymbol{\Sigma}_{H_1}\mathbf{w}_\text{o}\right], \tag{18}$$

in which π_0 and π_1 denote the *a priori* probabilities of occurrence of H_0 and H_1, respectively. Note that the matrix $\boldsymbol{\Sigma}_{H_1}$ is the equivalent expression of $\boldsymbol{\Sigma}_{H_0}$ for hypothesis H_1. If one assumes that π_0 and π_1 are known parameters [14], then one can obtain instantaneous estimates of such statistics by using the updated vector $\mathbf{w}(k+1)$ and the current parameters $\boldsymbol{\mu}(k)$ and $\boldsymbol{\Sigma}(k)$ in Eqs. (17) and (18).

By doing so, an iterative adaptation for the threshold $\bar{\gamma}(k+1)$, as a function of the second-order statistic estimate $\hat{\sigma}_\nu^2(k)$, is proposed at each SU node:

$$\bar{\gamma}(k+1) = \alpha\bar{\gamma}(k) + (1-\alpha)\sqrt{\beta\hat{\sigma}_\nu^2(k)}, \tag{19}$$

where $\alpha \in [0, 1]$ is a forgetting factor and $\beta \in \mathbb{R}_+$ is a constant carefully chosen to guarantee good update savings and robustness to errors in the reference signal $\hat{r}$ [10]. Note that the time-varying threshold in Eq. (19) is capable to follow dynamic environments as $\hat{\sigma}_\nu^2(k)$ is updated with the instantaneous $\boldsymbol{\mu}(k)$ and $\boldsymbol{\Sigma}(k)$.

V. Results

In this section, the performance of the proposed soft combiner (SM-NLMS) is assessed and compared with its closest competitor from the literature, namely the selective updating LMS (SU-LMS) [10]. Assuming that hypotheses H_0 and H_1 occur with equal probability, we have considered that each node obtains uncorrelated energy estimates and the number of Gaussian realizations is 500000. The desired signal of both adaptive filtering algorithms has been obtained using the OR-logic fusion rule presented in [10] and depicted in Fig. 1. The step size of the SU-LMS has been set to $\mu = 0.0001$. Due to the time-varying nature of the given scenario, we have used in the SM-NLMS algorithm the time-varying threshold $\bar{\gamma}(k)$ described in Section IV, where the parameters $\alpha = 0.995$ and $\beta = 3$ have been chosen [15].

The performance comparison takes into account two features:

1) The quality of the combiner, which is measured by the complementary receiver operating characteristic (C-ROC) curves depicted in Fig. 2.
2) The computational savings, which are quantified by the percentage of updatings during the transient (5% of the overall realizations) and steady states, as illustrated in Table I.

In Fig. 2(b) and Fig. 2(a), we assess the behavior of the algorithms in terms of the probability of miss-detection ($P_m = 1 - P_d$) against the probability of false alarm P_f for $M = 1, 3$, and 8 SUs. In both figures, we can observe that the performance gain of the cooperation among nodes is higher when the probability of false alarm is smaller. We can also see that SU-LMS and SM-NLMS algorithms have similar performances, as depicted in Fig. 2(b), and their performances are rather close to that of the optimal linear soft combiner proposed in [8] and shown in Fig. 2(a). On the other hand, the SM-NLMS yields much larger computational savings both in the transient and steady states than the SU-LMS as it is shown in Table I. The number of coeffficient updates in the transient period is always higher than in the steady state. In the worst case, this number is the 12.2% of the realizations for the SM-NLMS with 8 SUs. One can observe that during steady-state, the SM-NLMS only updates the weight coefficients the 5.9% and 10.8% of the time for $M = 3$ and 8, respectively. Therefore, a relative reduction of around 10% and 37% for $M = 3$ and $M = 8$, respectively, is achieved. As a consequence, we can conclude that SM-NLMS results in a more efficient solution than the SU-LMS since the former reduces the number of operations with no performance degradation.

TABLE I
Updating percentage at transient and steady states.

Transient/Steady (%)	$M=1$	$M=3$	$M=8$
SU-LMS	6.3 / 4.9	8.2 / 6.6	18.2 / 17.2
SM-NLMS	2.6 / 0.2	7.4 / 5.9	12.2 / 10.8

VI. Conclusions

This paper presented set-membership adaptive soft combining as a viable technique to be employed in cooperative spectrum sensing networks. We have used the well-known SM-NLMS algorithm employing the concept of constraint sets for cooperative spectrum sensing. One node collects the information of its neighbors and only performs a coefficient adaptation if its neighbors jointly offer relevant information. Simulation results showed that the proposed set-membership algorithm can reduce the number of operations of a previously proposed selective-updating algorithm with similar detection performance. In other words, a power comsumption reduction can be reached. Indeed, this feature is specially advantageous in distributed networks, in which signal processing is performed at each node with limited power.

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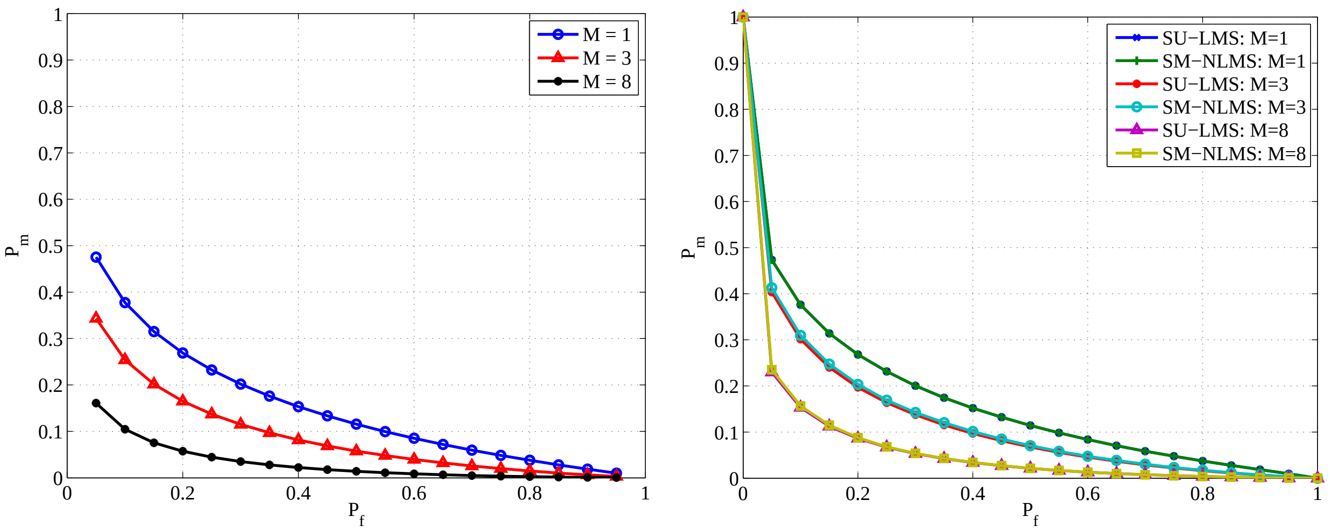

(a) Optimal linear solutions [8].

(b) SM-NLMS (proposal) *vs.* SU-LMS [10].

Fig. 2. Probability of miss-detection ($P_m = 1 - P_d$) versus the probability of false alarm (P_f) for different number of secondary users $M = 1, 3$, and 8. Specifically, the sensing noise levels and local SNRs are $\sigma^2 = 0.7$ and SNR= 10.4 dB for $M = 1$; $\sigma^2 = [0.7, 1, 0.9]$ and SNR= $[10.4, 9.3, 2.6]$ dB for $M = 3$, and $\sigma^2 = [0.7, 1, 0.9, 1.2, 1.8, 0.9, 1.3, 2]$ and SNR= $[10.4, 9.3, 2.6, 9.7, 3.6, -1.2, 6.7, 8.5]$ dB for $M = 8$.

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