One-Bit Radar Processing and Estimation with Time-Varying Sampling Thresholds

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***Abstract*—Target parameter estimation from noisy and quantized received signals is of paramount importance in radar applications. In this paper, we propose a novel method to estimate the unknown target parameters via one-bit sampling, where the samples are produced by comparing the received signal with a time-varying threshold. The proposed approach utilizes a weighted least-squares criterion to establish a connection to previous results in radar target estimation and signal processing. Several numerical examples are provided to demonstrate the effectiveness of the proposed approach.**

***Index Terms*—One-bit quantization, parameter estimation, radar, time-varying thresholds**

I. Introduction

In signal processing applications, the sampled signal amplitudes are typically rounded or *quantized* to the nearest predefined levels by employing analog-to-digital converters (ADCs). In the most benign setting, a very large number of quantization levels is required in order to represent the original continuous signal. However, this makes the sampling process impractical for modern use: In many applications such as spectral sensing for cognitive radio [1], cognitive radars [2], radio astronomy [3], automotive short-range radars [4], and driver assistant systems [5] the signals of interest have large bandwidths, and may pass through several RF chains that require using many ADCs. Moreover, the overall power consumption and the cost of ADCs increase exponentially with the number of quantization bits [6]. This drawback vitalizes the idea of using fewer bits for sampling in higher frequencies. The most extreme case would be to reduce the number of quantization bits to one, which makes the ADC behave as a simple comparator. This allows for sampling at a very high rate, with significantly lower cost and energy consumption compared to conventional ADCs [6].

Note that the high sampling rates afforded by one-bit ADCs may enable future sensing systems to recover the target scene with a higher resolution. The problem of parameter estimation using one-bit samples has been studied in recent years from different perspectives by revisiting classical problems in statistical signal processing [7]–[9], compressive sensing [10]–[19] and radar processing [20]. The idea of one-bit compressive sensing was first coined in [10] and further extended in [17] and [18]. Until recently, many of the researchers approached the problem of estimating signal parameters by comparing the signal with a fixed threshold, usually zero. This introduces difficulties in the recovery of the signal amplitude. However, in recent works, methods have been proven to efficiently estimate the signal parameters using the one-bit sampled data with time-varying thresholds [19], [21]–[24]. This idea has been further studied in different applications such as in massive MIMO scenarios [25], [26] and low-rank matrix recovery with partial information [27].

In this paper, we study the problem of target parameter estimation using the one-bit sampled data generated at the radar receiver. We develop an approach to estimate the target parameters from one-bit sampled data when the time-varying thresholds at the ADCs can be tuned based on *a priori* information on the transmit signal, and noise/clutter statistics. The proposed approach relies on the weighted least-squares criterion to form an optimization problem, which can then be efficiently solved to estimate the received signal as well as the target scattering coefficient. In particular, we show that the approach can successfully recover the parameters of interest for stationary targets.

Notation: We use bold lowercase letters for vectors/sequences and bold uppercase letters for matrices. $(\cdot)^H$ denotes the vector/matrix Hermitian transpose. $\Re\{\mathbf{x}\}$ and $\Im\{\mathbf{x}\}$ denote the real and imaginary parts of $\mathbf{x}$. The symbol $\odot$ stands for the Hadamard (element-wise) product of matrices.

II. Data Model and Problem Formulation

Let $\mathbf{s}$ denote the radar transmit sequence of length N,

$$\mathbf{s} = \begin{bmatrix} s_1 & s_2 & \dots & s_N \end{bmatrix}^T, \tag{1}$$

that is used to modulate the train of pulses. The received baseband signal will satisfy the following equation [28], [29]:

$$\mathbf{y} = \mathbf{A}^H \boldsymbol{\alpha} + \boldsymbol{\epsilon} \tag{2}$$

where

$$\mathbf{A}^H = \begin{bmatrix} s_1 & 0 & \dots & 0 & s_N & s_{N-1} & \dots & s_2 \\ s_2 & s_1 & \dots & \vdots & 0 & s_N & \dots & \vdots \\ \vdots & \vdots & \ddots & 0 & \vdots & \vdots & \ddots & s_N \\ s_N & s_{N-1} & \dots & s_1 & 0 & 0 & \dots & 0 \end{bmatrix}, \tag{3}$$

$$\boldsymbol{\alpha} = \begin{bmatrix} \alpha_0 & \alpha_1 & \dots & \alpha_{N-1} & \alpha_{-(N-1)} & \dots & \alpha_{-1} \end{bmatrix}^T, \tag{4}$$

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in which the parameter α_0 is the scattering coefficient of the current range cell, $\{\alpha_k\}_{k\neq 0}$ are the scattering coefficients of adjacent range cells contributing to clutter, and $\boldsymbol{\epsilon}$ is the interference term that accounts for noise. By using one-bit ADCs at the receiver, the sampled baseband signal can be written as:

$$\begin{aligned}\boldsymbol{\gamma}_r &= \operatorname{sgn}\left(\Re\{\mathbf{A}^H\boldsymbol{\alpha}+\boldsymbol{\epsilon}-\boldsymbol{\lambda}\}\right),\\ \boldsymbol{\gamma}_i &= \operatorname{sgn}\left(\Im\{\mathbf{A}^H\boldsymbol{\alpha}+\boldsymbol{\epsilon}-\boldsymbol{\lambda}\}\right),\\ \boldsymbol{\gamma} &= \tfrac{1}{\sqrt{2}}(\boldsymbol{\gamma}_r + j\boldsymbol{\gamma}_i),\end{aligned} \tag{5}$$

where $\boldsymbol{\lambda}$ is the complex-valued threshold level at the sampler which can be modified. In addition, we assume that

$$\begin{aligned}\mathbb{E}\{\boldsymbol{\epsilon}\boldsymbol{\epsilon}^H\} &= \boldsymbol{\Gamma},\\ \mathbb{E}\{|\alpha_k|^2\} &= \beta, \quad k\neq 0,\end{aligned} \tag{6}$$

where the interference covariance matrix $\boldsymbol{\Gamma}$, and the average clutter power β are known. Moreover, we assume that the clutter coefficients and interference term, $\boldsymbol{\epsilon}$, have zero mean and $\{\alpha_k\}_{k\neq 0}$ are independent of each other and of $\boldsymbol{\epsilon}$. When the received signal $\mathbf{y}$ is *available*, the estimation of the scattering coefficient of the current range cell α_0 can be done via a matched filter (MF). Nevertheless, a better estimate of α_0 in terms of the mean square error (MSE) can be achieved by applying a mismatched filter (MMF) to the received signal. The MMF estimate of α_0 is given by

$$\hat{\alpha}_0 = \frac{\mathbf{w}^H\mathbf{y}}{\mathbf{w}^H\mathbf{s}} \tag{7}$$

where $\mathbf{w}\in\mathbb{C}^N$ is the MMF vector. With all the aforementioned assumptions, the MSE of (7) can be derived as

$$\operatorname{MSE}(\hat{\alpha}_0) = \mathbb{E}\left\{\left|\frac{\mathbf{w}^H\mathbf{y}}{\mathbf{w}^H\mathbf{s}} - \alpha_0\right|^2\right\} = \frac{\mathbf{w}^H\mathbf{R}\mathbf{w}}{|\mathbf{w}^H\mathbf{s}|^2} \tag{8}$$

where

$$\mathbf{R} = \beta \sum_{0<|k|\leq (N-1)} \mathbf{J}_k\mathbf{s}\mathbf{s}^H\mathbf{J}_k^H + \boldsymbol{\Gamma}, \tag{9}$$

and $\{\mathbf{J}_k\}$ are the shift matrices defined by

$$\mathbf{J}_k = \mathbf{J}_{-k}^H = \begin{bmatrix} 0 & \dots & 0 & 1 & \dots & 0\\ \vdots & & & & \ddots & \\ & & & & & 1\\ \underbrace{0 \;\; \dots \;\; 0}_{k} & & & \dots & & \end{bmatrix}. \tag{10}$$

Note that (8) does not directly depend on $\mathbf{y}$, but only on the transmit sequence, the MMF vector and other *a priori* known clutter/interference statistics. Particularly, for a given transmit sequence $\mathbf{s}$, the minimizer $\mathbf{w}$ of the MSE critetion in (8) is given in closed form as [28], [29]

$$\mathbf{w} = \mathbf{R}^{-1}\mathbf{s}. \tag{11}$$

However, a filtering approach as described in (7) to produce an estimate of α_0 requires a knowledge of $\mathbf{y}$, which is not available in a one-bit sampling scenario. In the following, we discuss estimation approaches for recovery of $\mathbf{y}$ and α_0 using the one-bit data, namely $\boldsymbol{\gamma}_r$ and $\boldsymbol{\gamma}_i$.

III. Bussgang Theorem-Aided Estimation

This section briefly describes some statistical properties of one-bit quantization and then introduces a target paramter estimation method based on these properties. The introduced statistical approach will be later used for comparison with the proposed method in Section IV.

The autocorrelation of one-bit sampled signals has been studied in [32]. Let $Y(t)$ be a real-valued, scalar and stationary Gaussian process that goes through the one-bit sampling process $Z(t) = \operatorname{sgn}(Y(t))$. The autocorrelation function of $Z(t)$, denoted by $R_Z(\tau)$ is given by

$$C_Z(\tau) = \mathbb{E}\{Z(t+\tau)Z(t)\} = \frac{2}{\pi}\sin^{-1}\bar{C}_Y(\tau) \tag{12}$$

with $\bar{C}_Y(\tau) = C_Y(\tau)/C_Y(0)$ being the normalized autocorrelation function of $Y(t)$. The Bussgang theorem [33] further shows that the cross-correlation of $Y(t)$ and $Z(t)$ is proportional to the autocorrelation of $Y(t)$, i.e. $C_{ZY}(\tau) = \mu C_Y(\tau)$. The proportion factor μ depends solely on the power of $Y(t)$. This can be very helpful as it makes the output, $Z(t)$, a linear function of $Y(t)$ in terms of the second order statistics.

A complex-valued vectorized alternative to the above result was presented in [34]. For a complex vector $\mathbf{y}$, the one-bit measurement vector is obtained as

$$\boldsymbol{\gamma} = \frac{1}{\sqrt{2}}\operatorname{sgn}(\mathbf{y}) \triangleq \frac{1}{\sqrt{2}}\left[\operatorname{sgn}(\Re(\mathbf{y})) + j\operatorname{sgn}(\Im(\mathbf{y}))\right] \tag{13}$$

where the multiplicative factor $1/\sqrt{2}$ is used to normalize the power in $\boldsymbol{\gamma}$. The normalized autocorrelation matrix of $\mathbf{y}$ is given by

$$\bar{\mathbf{C}}_\mathbf{y} = \mathcal{N}(\mathbf{C}_\mathbf{y}) \triangleq \mathbf{W}^{-1/2}\mathbf{C}_\mathbf{y}\mathbf{W}^{-1/2} \tag{14}$$

with $\mathbf{W} = \mathbf{C}_\mathbf{y}\odot\mathbf{I}$ containing only the diagonal entries of $\mathbf{C}_\mathbf{y}$. In this case, the following covariance equality holds:

$$\bar{\mathbf{C}}_\mathbf{y} = \sin\left(\frac{\pi}{2}\mathbf{C}_{\boldsymbol{\gamma}}\right). \tag{15}$$

To use the above result in our application with time-varying thresholds, we can simply derive the covariance matrix of the sampled signal when the threshold is already deducted from it, viz.

$$\mathbf{C}_{\mathbf{y}-\boldsymbol{\lambda}} = |\alpha_0|^2\mathbf{s}\mathbf{s}^H + \boldsymbol{\lambda}\boldsymbol{\lambda}^H + \mathbf{R} - 2\,\Re\{\alpha_0\,\mathbf{s}\boldsymbol{\lambda}^H\}. \tag{16}$$

Consequently, one can recover the unknown α_0 by minimizing the non-convex criterion,

$$\left\|\bar{\mathbf{C}}_{\mathbf{y}-\boldsymbol{\lambda}} - \mathcal{N}\left(|\alpha_0|^2\mathbf{s}\mathbf{s}^H + \boldsymbol{\lambda}\boldsymbol{\lambda}^H + \mathbf{R} - 2\,\Re\left\{\alpha_0\,\mathbf{s}\boldsymbol{\lambda}^H\right\}\right)\right\|_F$$

with respect to α_0, in which the normalized covariance matrix $\bar{\mathbf{C}}_{\mathbf{y}-\boldsymbol{\lambda}}$ is estimated based on (15) and only one obervation or *snapshot* of $\boldsymbol{\gamma}$ in (5).

IV. The Proposed Method

In this section, we discuss our proposed approach to recover both $\mathbf{y}$ and α_0 using the one-bit sampled radar signal. The steps of the proposed approach is summarized in Algorithm 1 for reader's convenience.

A. Estimation of Radar Parameters

We begin our discussion by considering the weighted least-squares objective:

$$Q(\mathbf{y},\alpha_0)=(\mathbf{y}-\alpha_0\mathbf{s})^H\mathbf{R}^{-1}(\mathbf{y}-\alpha_0\mathbf{s}). \tag{17}$$

Note that the above objective has the following properties:

1) In contrast to the mismatched filter, it does not assume a knowledge of $\mathbf{y}$. Indeed, (17) maintains its dependence on $\mathbf{y}$ which will enable us to recover $\mathbf{y}$ as well.
2) It is easy to verify that the optimal α_0 of (17) for any given $\mathbf{y}$ is exactly the same as the mismatched filter presented in (7).
3) It can facilitate a joint estimation of $\mathbf{y}$ and α_0 as it enforces the structure in (2) and (5). Note that (17) penalizes the model mismatch depending on the mismatch statistics as

$$\mathbf{y}-\alpha_0\mathbf{s}=\tilde{\mathbf{A}}^H\tilde{\boldsymbol{\alpha}}+\boldsymbol{\epsilon}, \tag{18}$$

where $\tilde{\mathbf{A}}$ and $\tilde{\boldsymbol{\alpha}}$ are generated from $\mathbf{A}$ and $\boldsymbol{\alpha}$ with their first column and first entry removed, respectively. Particularly, it can be shown that the covariance matrix of the mismatch $\tilde{\mathbf{A}}^H\tilde{\boldsymbol{\alpha}}+\boldsymbol{\epsilon}$ is equal to $\mathbf{R}$:

$$\begin{aligned}&\mathbb{E}\left\{\left(\tilde{\mathbf{A}}^H\tilde{\boldsymbol{\alpha}}+\boldsymbol{\epsilon}\right)\left(\tilde{\mathbf{A}}^H\tilde{\boldsymbol{\alpha}}+\boldsymbol{\epsilon}\right)^H\right\}\\ =\;&\mathbb{E}\left\{\tilde{\mathbf{A}}^H\tilde{\boldsymbol{\alpha}}\tilde{\boldsymbol{\alpha}}\tilde{\mathbf{A}}\right\}+\mathbb{E}\left\{\boldsymbol{\epsilon}\boldsymbol{\epsilon}^H\right\}\\ =\;&\beta\sum_{0<|k|\leq(N-1)}\mathbf{J}_k\mathbf{s}\mathbf{s}^H\mathbf{J}_k^H+\boldsymbol{\Gamma}\\ =\;&\mathbf{R}.\end{aligned} \tag{19}$$

4) By utilizing the proposed criterion, one can estimate the received signal $\mathbf{y}$, along with the desired scattering coefficient. This lays the ground for classical processing methods that rely on the knowledge of $\mathbf{y}$ to be used for various radar information processing applications.

Observe that by substituting the optimal value of α_0 (denoted by $\hat{\alpha}_0$) for a fixed $\mathbf{y}$, (17) may be rewritten as

$$\begin{aligned}Q(\mathbf{y})&=Q(\mathbf{y},\hat{\alpha}_0) \qquad (20)\\ &=\mathbf{y}^H\left(\mathbf{I}-\frac{\mathbf{s}\mathbf{w}^H}{\mathbf{w}^H\mathbf{s}}\right)^H\mathbf{R}^{-1}\left(\mathbf{I}-\frac{\mathbf{s}\mathbf{w}^H}{\mathbf{w}^H\mathbf{s}}\right)\mathbf{y}.\end{aligned}$$

As a result, the joint estimation problem of finding α_0 and $\mathbf{y}$ reduces to

$$\begin{aligned}\min_{\mathbf{y}}\quad&\mathbf{y}^H\left[\left(\mathbf{I}-\frac{\mathbf{s}\mathbf{w}^H}{\mathbf{w}^H\mathbf{s}}\right)^H\mathbf{R}^{-1}\left(\mathbf{I}-\frac{\mathbf{s}\mathbf{w}^H}{\mathbf{w}^H\mathbf{s}}\right)\right]\mathbf{y} \qquad (21)\\ \text{s.t.}\quad&\boldsymbol{\Omega}_r\left(\mathbf{y}_r-\boldsymbol{\lambda}_r\right)\geq\mathbf{0},\\ &\boldsymbol{\Omega}_i\left(\mathbf{y}_i-\boldsymbol{\lambda}_i\right)\geq\mathbf{0},\end{aligned}$$

where $(\mathbf{y}_r,\mathbf{y}_i)$ and $(\boldsymbol{\lambda}_r,\boldsymbol{\lambda}_i)$ denote the real and imaginary parts of $\mathbf{y}$ and $\boldsymbol{\lambda}$, respectively, and we have $\boldsymbol{\Omega}_r=\mathbf{Diag}(\gamma_r)$, $\boldsymbol{\Omega}_i=\mathbf{Diag}(\gamma_i)$, with $\mathbf{Diag}(.)$ being a diagonal matrix with diagonal entries equal to those of its vector argument. The above optimization problem is a convex linearly-constrained quadratic program and can be solved efficiently, e.g., by interior point methods. Once the optimal $\mathbf{y}$ is found, the optimal α_0 can be found using the mismatched filter in (7).

Algorithm 1 One-Bit Radar Processing and Estimation

Step 0: Initialize $\mathbf{s}$, and set $\boldsymbol{\lambda}$ arbitrarily or according to (22)-(23).
Step 1: Compute the optimal MMF vector $\mathbf{w}$ according to (11).
Step 3: Compute the vector $\mathbf{y}$ by solving (21).
Step 4: Estimate the target scattering coefficient α_0 using (7).
Step 5: In case of tracking, set $\boldsymbol{\lambda}$ according to (22)-(23) and goto Step 1.

Remark 1 (Transition to NNLS): Note that we can easily transition from (21) to a non-negative least-squares (NNLS) optimization problem. This only requires a slight change of variables; namely $\tilde{\mathbf{y}}_r=\boldsymbol{\Omega}_r\left(\mathbf{y}_r-\boldsymbol{\lambda}_r\right)$ and $\tilde{\mathbf{y}}_i=\boldsymbol{\Omega}_i\left(\mathbf{y}_i-\boldsymbol{\lambda}_i\right)$ adding up to $\tilde{\mathbf{y}}=\tilde{\mathbf{y}}_r+j\tilde{\mathbf{y}}_i$. Therefore, fast NNLS approaches can be used to speed up the recovery; see [35] for details. ■

B. Determination of Time-Varying Thresholds

— *Sampling with a Single One-Bit ADC:* From an information theoretic viewpoint, in order to collect the *most* information on $\mathbf{y}$, one could expect $\boldsymbol{\lambda}$ to be set in such a way that by considering the *a priori* information, observing any of the two outcomes in the set $\{-1,+1\}$ at the output of the one-bit sampler for a single sample has the same likelihood. In a general case, $\boldsymbol{\lambda}$ is expected to partition the set of likely events into two subsets with similar *cardinality*. When the pdf of the received signal follows a Gaussian distribution, this goal is achieved by setting $\boldsymbol{\lambda}$ as close as possible to the expected value of $\mathbf{y}$. More precisely, we choose:

$$\boldsymbol{\lambda}=\mathbb{E}\left\{\alpha_0\right\}\mathbf{s}. \tag{22}$$

In other words, the choice of $\boldsymbol{\lambda}$ will be governed by our *future* expectation of the value of α_0. This is particularly pertinent to target tracking scenarios.

— *Sampling with Multiple One-Bit ADCs:* Assuming that K ADCs are used in parallel and the thresholds are set *a priori*, in the single sample case, the thresholds are optimal if they partition the set of likely events into $K+1$ subsets with similar *cardinality*. The determination of the thresholds will be even more difficult when the number of samples or the number of ADCs grow large. However, a close *approximation* of the optimal threshold vectors $\{\boldsymbol{\lambda_k}\}_{k=1}^{K}$ can be obtained by assuming $\{\boldsymbol{\lambda_k}\}_{k=1}^{K}$ to be random variables. In particular, a good set of random sampling threshold vectors $\{\boldsymbol{\lambda_k}\}_{k=1}^{K}$ should still mimic the behavior of $\mathbf{y}$; i.e., we generate $\{\boldsymbol{\lambda_k}\}_{k=1}^{K}$ as a (i) set of random vectors similar to $\mathbf{y}$ (ii) that have the same (Gaussian) distribution:

$$\begin{aligned}\mathbb{E}\left\{\boldsymbol{\lambda}\right\}&=\mathbb{E}\left\{\alpha_0\right\}\mathbf{s},\\ \mathrm{Cov}(\boldsymbol{\lambda})&=\mathbb{E}\left\{|\alpha_0|^2\right\}\mathbf{s}\mathbf{s}^H+\mathbf{R}.\end{aligned} \tag{23}$$

V. Numerical Results

In this section, we examine the performance of the proposed approach by providing comparisons with the Bussgang-aided

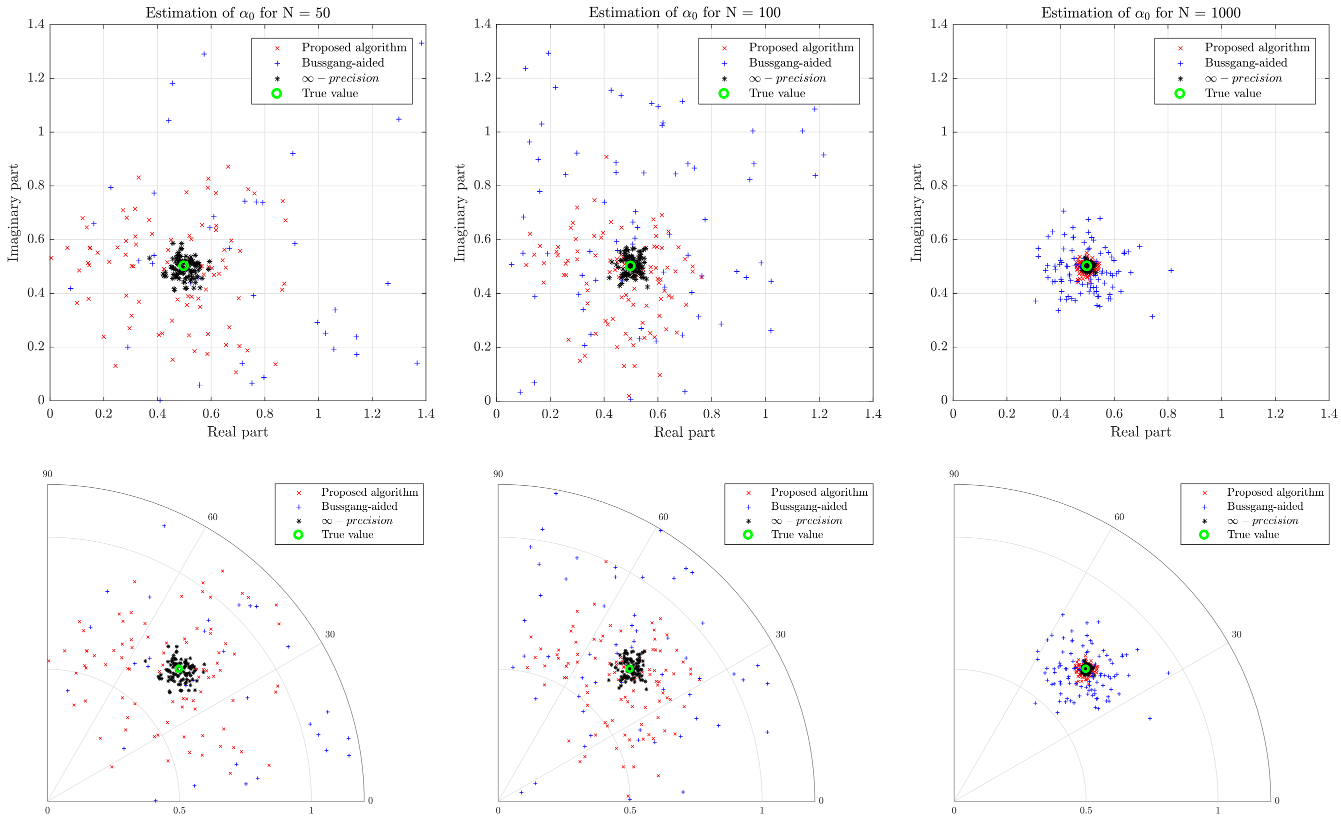

Fig. 1: Performance comparison of the proposed algorithm, Bussgang-aided approach, and the $\infty - precision$ case when estimating the target scattering coefficient α_0 for various lengths of the transmit/receive sequence $N \in \{50, 100, 1000\}$. The upper and lower plots show the results in complex Cartesian and polar planes. The proposed one-bit estimation approach presents a satisfactory performance, closing its gap with the $\infty - precision$ case as N grows large.

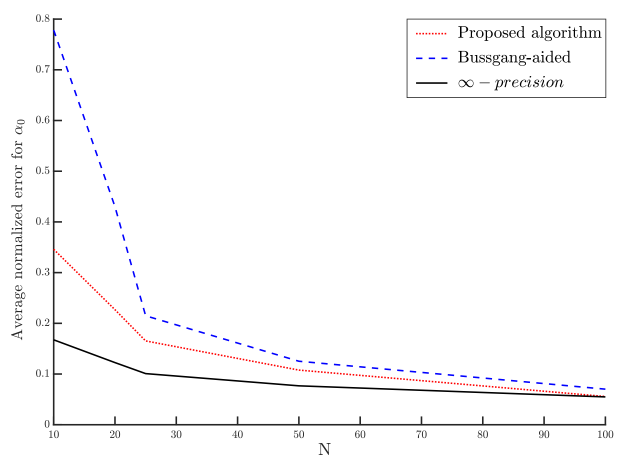

Fig. 2: Average normalized error of the estimated α_0 vs. N.

estimation method discussed in Section III, as well as the case in which the received signal $\mathbf{y}$ is available with virtually infinite precision (denoted by $\infty - precision$). We assume the noise to be additive and white with variance 0.1. The average clutter power β is set to 0.1. Moreover, the transmit sequence $\mathbf{s}$ is assumed to have a peak-to-average power ratio (PAR) of unity and is optimized using the approach proposed in [29].

For the sake of comparison, we run each of the aforementioned algorithms 50 times. The results of the proposed algorithm and the other methods when estimating α_0 are depicted in Fig 1 for $N = 50, 100$, and 1000. The upper plots show the results along with the true value of α_0 in the complex plane, while the lower plots show the same data in polar format for further examination. Additionally, Fig. 2 shows the average normalized error of $\hat{\alpha}_0$ for various N, defined by the ratio $|\alpha_0 - \hat{\alpha}_0|/|\alpha_0|$. From both figures, it can be observed that the proposed algorithm presents a better performance compared with the Bussgang-aided approach. Moreover, as N grows large, the estimation performance of the proposed method approaches that of the $\infty - precision$ case. As expected, all methods show improvement in estimation performance with increasing N.

VI. Conclusion

Conventional sampling using many quantization levels can be very power-consuming and costly as modern high frequency applications demand even higher sampling rates. To circumvent such issues, we turned our attention to limiting the quantization bits to only one. An estimation approach based on one-bit samples was formulated. It was shown that one-bit sampling can effectively be used in radars for target parameter estimation. Numerical examples were provided to exhibit the effectiveness of the proposed method.

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