Efficient Velocity Estimation in Distributed RF Sensing

Fangzhou Wang, Xudong Zhang, and Hongbin Li
ECE Department, Stevens Institute of Technology
Hoboken, NJ 07030, USA
email: fwang11@stevens.edu; xzhan24@stevens.edu; hli@stevens.edu

Braham Himed
AFRL/RYMS
Dayton, OH 45433 USA
email: braham.himed@us.af.mil

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***Abstract*—In this paper, we examine the problem of velocity estimation for a moving object using distributed measurements. The system employs a non-cooperative transmitter and multiple receivers to collect targets echoes. The problem is formulated by modelling the unknown transmitted waveform as a deterministic process. The exact maximum likelihood estimator (MLE) is developed which requires a multi-dimensional search procedure. To reduce the computational load, an efficient two-step estimator (TSE) is proposed. The TSE first finds the maximum likelihood estimates of pairwise differences of the Doppler frequencies observed by the receivers. Then, the target velocity can be estimated from the frequency differences in closed-form. We show that the maximum likelihood estimation of each frequency difference reduces to a cross-correlation process followed by peak finding, which can efficiently be implemented by the fast Fourier transform (FFT). As a result, the TSE is significantly more efficient than the MLE. Numerical results show the TSE achieves a similar estimation accuracy as that of the MLE except for very low signal-to-noise ratio (SNR) scenarios.**

***Index Terms*—Multistatic passive radar, target velocity estimation, maximum likelihood, efficient implementation.**

I. Introduction

Parameter estimation using distributed sensors, which exploits ambient non-cooperative illuminators of opportunity (IOs) as transmitters, has attracted significant attention in recent years [1]–[5]. The available sources include frequency modulation (FM) radio, television, digital audio/video broadcasting (DAB/DVB-T), cellular signals, and others [6]–[9]. Besides the wide availability of potential sources, passive sensing has several advantages compared with active sensing, including less vulnerability to interference and no additional radio frequency (RF) pollution to the electromagnetic environment.

Unlike a monostatic or bistatic sensing system, where only a single pair of transmitter-receiver is employed, a distributed configuration enables the system to view the target from several different angles simultaneously, which offers spatial or geometric diversity needed to improve the sensing capability [10]–[14]. In particular, targets often show significant azimuth-selective backscattering with tens of dB of fluctuation in their radar cross section (RCS). Therefore, it would be more challenging for a monostatic or bistatic sensing system to detect a moving object with an unfavorable geometry. The spatial diversity offered by a distributed sensing network with widely separated antennas was discussed in [10] to solve the target velocity estimation problem while [15] proposed a parametric moving target detector for a distributed sensing network. A multi-target tracking problem using a distributed sensor network was considered in [16], where by discretizing the position-velocity space, the problem was turned into a group sparse problem and a two-step sequential approach was proposed to track multiple targets. Meanwhile, distributed detection was examined in [17] by exploiting the correlation of the transmitted waveform and new detectors were proposed for distributed sensing network with synchronization errors in [18].

Motion parameter estimation of ground moving targets has been extensively studied in the context of conventional active sensing. Time-frequency analysis was first discussed in [19] for moving target estimation based on its Doppler signature. A fast estimation method based on an adjacent cross-correlation function is proposed in [20], where an iterative process is employed to remove the range migration and reduce the order of Doppler frequency migration. In recent years, a number of studies considered the estimation of target motion parameters using distributed passive sensor networks [21]–[23]. Specifically, a modified Cramer-Rao lower bound was proposed in [21] for target parameter estimation using multiple transmitters and multiple receivers. In [22], the motion parameters were estimated based on the observed Doppler signatures corresponding to multiple illuminators. Additionally, [23] presented a maximum likelihood (ML) estimate of the unknown position and velocity vector of a moving target using a distributed sensor network. In both [22] and [23], the transmitted signals are assumed to have been perfectly reconstructed from the direct path observation after successful demodulation.

In this paper, we assume the transmitted waveform to be an unknown deterministic process. Following the deterministic assumption, we develop the exact maximum likelihood estimator (MLE) which requires a multi-dimensional search procedure. Next, we propose an efficient two-step estimator (TSE) to simplify the computational load by dividing the observation from different receivers into pairs and find the ML estimates of pairwise difference of the Doppler frequencies. For each pair of observation, the ML estimation of the frequency difference turns out to be a cross-correlation process

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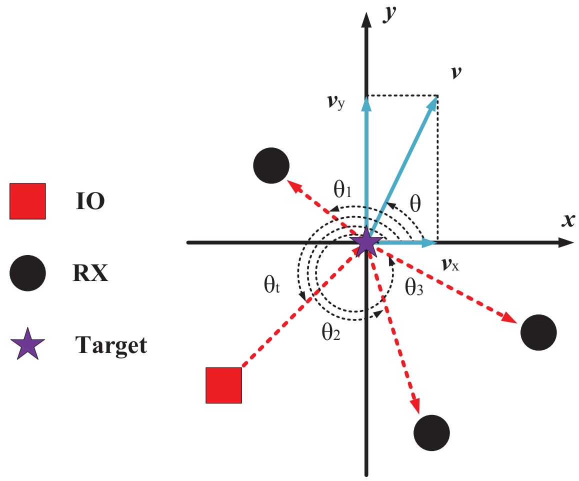


Fig. 1. The configuration for a distributed sensor network.

followed by peak finding, which can be efficiently obtained using a 1-dimensional (1-D) fast Fourier transform (FFT). Then, the target velocity can be estimated from frequency differences in closed-form. Numerical results show that the performance of the computationally efficient TSE is very close to that of the grid search based MLE, except for very low signal-to-noise ratio (SNR) scenarios. In addition, the TSE is faster than the MLE-based technique.

The remainder of the paper is organized as follows. Section II describes the system model and formulates the problem of interest. Section III presents the proposed MLE and TSE estimators for target velocity estimation. Numerical results and discussions are included in Section IV. Finally, Section V concludes this work.

Notation: Throughout the paper, scalars are denoted by non-boldface type, vectors (matrices) are denoted by boldface lower (upper) case letters, and all vectors are column vectors. Superscripts $(\cdot)^T$, $(\cdot)^*$, and $(\cdot)^H$ denote transpose, complex conjugate, and complex conjugate transpose, respectively. $[\cdot]_m$ denotes the m-th element of a vector. $\odot$ stands for the Hadamard products. $\|\cdot\|$ is the Frobenius norm, and $\text{tr}\{\cdot\}$ denotes the trace of a matrix.

II. Signal Model

A distributed sensor network geometry is shown in Fig. 1. It consists of a non-cooperative transmitter and several receive (RX) antennas which collect echoes from a moving object that is illuminated by the transmitter. The RXs are stationary and their locations are assumed known. For simplicity, we assume the target, transmitter, and RXs are located on a two-dimensional (2-D) plane. An extension to the more general three-dimensional (3-D) case is possible. Let $\mathbf{y}_i \in \mathbb{C}^{N\times 1}$ denotes the N observed signal samples at the i-th receiver. Then, the digitized received signal model can be expressed as:

$$\mathbf{y}_i = \gamma_i \mathbf{A}\big(f_i(\mathbf{v})\big)\mathbf{x} + \mathbf{n}_i,\ i = 1,\ \cdots,\ I, \tag{1}$$

where γ_i is an unknown parameter that integrates the channel coefficient and target amplitude associated with the i-th receiver; $f_i(\mathbf{v})$ is the Doppler frequency observed by the i-th receiver with respect to (w.r.t.) a moving target with velocity $\mathbf{v} \triangleq (v_x, v_y)$; $\mathbf{A}(x)$ is a diagonal matrix with diagonal entries $[\mathbf{A}(x)]_{p,p} = e^{\jmath 2\pi(p-1)T_\text{s}x}$, where $T_\text{s} = 1/f_\text{s}$ denotes the sampling interval; $\mathbf{x}$ is the deterministic unknown transmitted waveform; $\mathbf{n}_i$ is a zero-mean white Gaussian noise with covariance matrices $\sigma_i^2\mathbf{I}$. The relationship between the target velocity $\mathbf{v}$ and its Doppler frequency can be obtained by using the geometry depicted in Fig. 1. The normalized bistatic Doppler frequency is given by

$$f_i(\mathbf{v}) = \frac{T_\text{s}}{\lambda}\frac{d}{dt}(R_\text{t} + R_{\text{r},i}),\quad i = 1,\ \cdots,\ I, \tag{2}$$

where λ denotes the wavelength of the carrier signal, R_t is the distance between the transmitter and the target, and $R_{\text{r},i}$ is the distance between the i-th receiver and the target. The two ranges can be expressed as

$$R_\text{t} = -(v_x\cos(\theta_t - \pi) + v_y\cos(3\pi/2 - \theta_t))dt, \tag{3}$$

and

$$R_{\text{r},i} = -(v_x\cos(\pi - \theta_i) - v_y\cos(\theta_i - \pi/2))dt, \tag{4}$$

where θ_t is the azimuth angle of the transmitter, θ_i is the azimuth angle of the i-th receiver, $v_x = |\mathbf{v}|\cos\theta$, and $v_y = |\mathbf{v}|\sin\theta$. θ is the unknown moving direction of the target. Substituting (3) and (4) back into (2), we have the normalized Doppler frequency $f_i(\mathbf{v})$ given by

$$f_i(\mathbf{v}) = \frac{T_\text{s}}{\lambda}(v_x\cos\theta_t + v_y\sin\theta_t + v_x\cos\theta_i + v_y\sin\theta_i). \tag{5}$$

For simplicity, we will henceforth sometimes write the matrix $\mathbf{A}\big(f_i(\mathbf{v})\big)$ as $\mathbf{A}(f_i)$. The problem of interest is to estimate the velocity of the moving target from the observations $\mathbf{y}_i$.

III. Proposed Methods

In this section, we first develop the exact maximum likelihood estimator for the target velocity using observations from all receivers. Next, a computationally efficient two-step estimator is introduced to reduce the computational load.

A. Exact MLE

Given observations $\mathbf{y} = [\mathbf{y}_1^T,\ \cdots,\ \mathbf{y}_I^T]^T$, the likelihood function of $\mathbf{y}$ is

$$p(\mathbf{y}|\boldsymbol{\theta}) = \frac{1}{(\pi\sigma^2)^{NI}}\exp\Big\{-\frac{1}{\sigma^2}\sum_{i=1}^{I}\big(\|\mathbf{y}_i - \gamma_i\mathbf{A}(f_i)\mathbf{x}\|^2\big)\Big\}, \tag{6}$$

where $\boldsymbol{\theta} = [\boldsymbol{\gamma},\ \mathbf{v},\ \mathbf{x},\ \sigma^2]^T$ and $\boldsymbol{\gamma} = [\gamma_1,\ \cdots,\ \gamma_I]^T$. Then, the log-likelihood function (LLF) can be written as

$$\log p(\mathbf{y}|\boldsymbol{\theta}) = -NI\log(\pi\sigma^2) - \frac{1}{\sigma^2}\sum_{i=1}^{I}\|\mathbf{y}_i - \gamma_i\mathbf{A}(f_i)\mathbf{x}\|^2. \tag{7}$$

The ML estimates of the unknown parameters can be obtained by maximizing the LLF and are given by

$$\max_{\boldsymbol{\theta}} \quad \log p(\mathbf{y}|\boldsymbol{\theta}). \tag{8}$$

The maximization can be carried out sequentially w.r.t. each parameter group, including the amplitudes $\boldsymbol{\gamma}$, the target velocity $\mathbf{v}$, the waveform $\mathbf{x}$, and the noise variance σ^2. For the amplitude parameters, the ML estimate can be obtained by taking the derivatives w.r.t. $\boldsymbol{\gamma}$ and σ^2, and setting them to zero:

$$\frac{\partial \log p(\mathbf{y}|\boldsymbol{\theta})}{\partial \gamma_i} = 0. \tag{9}$$

Solving the above equation leads to the estimate of γ_i:

$$\hat{\gamma_i} = \frac{\mathbf{x}^H \mathbf{A}(f_i)^H \mathbf{y}_i}{\mathbf{x}^H \mathbf{x}}. \tag{10}$$

Substituting (10) back into (7) gives

$$\begin{aligned} &\log p(\mathbf{y}|\mathbf{v},\ \mathbf{x},\ \sigma^2) = -NI \log(\pi\sigma^2) \\ &- \frac{1}{\sigma^2} \sum_{i=1}^{I} \big(\|\mathbf{y}_i\|^2 - \frac{\mathbf{x}^H \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{x}}{\mathbf{x}^H \mathbf{x}}\big). \end{aligned} \tag{11}$$

The ML estimate of σ^2 can be obtained by setting $\frac{\partial \log p(\mathbf{y}|\mathbf{v},\ \mathbf{x},\ \sigma^2)}{\partial \sigma^2} = 0$, and subsequently, the estimate is given by

$$\hat{\sigma^2} = \frac{1}{NI} \Big(\sum_{i=1}^{I} \big(\|\mathbf{y}_i\|^2 - \frac{\mathbf{x}^H \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{x}}{\mathbf{x}^H \mathbf{x}}\big) \Big). \tag{12}$$

Substituting (12) back into (11) and ignoring the constant terms that are not related to the unknown parameter $\mathbf{v}$ and $\mathbf{x}$, we have

$$\begin{aligned} \log &p(\mathbf{y}|\mathbf{v},\ \mathbf{x}) = -NI \log \Big(\sum_{i=1}^{I} \big(\|\mathbf{y}_i\|^2 \\ &- \frac{\mathbf{x}^H \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{x}}{\mathbf{x}^H \mathbf{x}}\big) \Big). \end{aligned} \tag{13}$$

Then, the ML estimate of $\mathbf{v}$ and $\mathbf{x}$ are obtained by maximizing:

$$\max_{\mathbf{v},\ \mathbf{x}} \quad \frac{\mathbf{x}^H \big(\sum_{i=1}^{I} \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \big) \mathbf{x}}{\mathbf{x}^H \mathbf{x}}, \tag{14}$$

which means that maximization w.r.t. $\mathbf{x}$ is equivalent to maximizing the Rayleigh quotient with some $\mathbf{v}$. The maximum of the cost function is the largest eigenvalue of $\sum_{i=1}^{I} \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i)$ and the corresponding eigenvector is the ML estimate of the transmitted waveform $\hat{\mathbf{x}}$. Hence, the ML estimate of $\mathbf{v}$ is given by

$$\hat{\mathbf{v}} = \arg \ \max_{\mathbf{v}} \lambda_{\text{max}} \Big(\sum_{i=1}^{I} \mathbf{A}\big(f_i(\mathbf{v})\big)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}\big(f_i(\mathbf{v})\big) \Big), \tag{15}$$

where $\lambda_{\text{max}}(\cdot)$ denotes the largest eigenvalue of a matrix. Since there is no known closed-form solution to (15), we consider a 2-D search of v_x and v_y for the target velocity estimation. In practice, we often employ a two-step search to obtain the ML estimate: divide the uncertain velocity interval into equally spaced points to carry out a coarse grid search to provide an initial estimate and then use a refined local search around the initial estimate.

B. Efficient TSE

Given the observations described by $\mathbf{y} = [\mathbf{y}_1^T, \cdots, \mathbf{y}_I^T]^T$, we need to use a brute force search over the 2-D parameter space to obtain the ML estimate of the velocity, which is computationally prohibitive. Next, we propose an efficient TSE to simplify the computational load by dividing the receivers into pairs and obtain estimates of the pairwise differences of the Doppler frequencies observed by the receivers. For simplicity, we consider the case with $I = 3$ receivers.We divide the observations into 3 groups $\mathbf{y}_{\text{A}} = [\mathbf{y}_1^T, \mathbf{y}_2^T]^T$, $\mathbf{y}_{\text{B}} = [\mathbf{y}_1^T, \mathbf{y}_3^T]^T$, and $\mathbf{y}_{\text{C}} = [\mathbf{y}_2^T, \mathbf{y}_3^T]^T$. For each observation group $[\mathbf{y}_i^T, \mathbf{y}_j^T]^T,\ i, j = 1, 2, 3,$ and $i \neq j$, it is clear that the ML estimate of f_i and f_j are given by

$$\{\hat{f}_i,\ \hat{f}_j\} = \arg \ \max_{f_i,\ f_j} \ \lambda_{\text{max}}(\boldsymbol{\Phi}), \tag{16}$$

where

$$\boldsymbol{\Phi} = \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) + \mathbf{A}(f_j)^H \mathbf{y}_j \mathbf{y}_j^H \mathbf{A}(f_j). \tag{17}$$

Since $\boldsymbol{\Phi}$ is the addition of two rank-one Hermitian matrices, it has at most two non-zero eigenvalues λ_1 and λ_2, assuming $\lambda_1 \geq \lambda_2$. Based on the property of the trace of a matrix and the fact that $\mathbf{A}(f_i)$ and $\mathbf{A}(f_j)$ are both unitary matrix, we have:

$$\begin{aligned} &\text{tr}(\boldsymbol{\Phi}) = \lambda_1 + \lambda_2 = \|\mathbf{y}_i\|^2 + \|\mathbf{y}_j\|^2 \\ &\text{tr}(\boldsymbol{\Phi}^2) = \lambda_1^2 + \lambda_2^2, \end{aligned} \tag{18}$$

where the second equality can be easily verified with the eigendecomposition of $\boldsymbol{\Phi}$. Meanwhile, we have

$$\begin{aligned} \boldsymbol{\Phi}^2 &= \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \\ &+ \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_j)^H \mathbf{y}_j \mathbf{y}_j^H \mathbf{A}(f_j) \\ &+ \mathbf{A}(f_j)^H \mathbf{y}_j \mathbf{y}_j^H \mathbf{A}(f_j) \mathbf{A}(f_i)^H \mathbf{y}_i \mathbf{y}_i^H \mathbf{A}(f_i) \\ &+ \mathbf{A}(f_j)^H \mathbf{y}_j \mathbf{y}_j^H \mathbf{A}(f_j) \mathbf{A}(f_j)^H \mathbf{y}_j \mathbf{y}_j^H \mathbf{A}(f_j), \end{aligned} \tag{19}$$

which leads to

$$\text{tr}(\boldsymbol{\Phi}^2) = \|\mathbf{y}_i\|^4 + 2|\mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_j)^H \mathbf{y}_j|^2 + \|\mathbf{y}_j\|^4. \tag{20}$$

Then, combining (18) and (20) gives:

$$\begin{aligned} \lambda_1 \lambda_2 = \frac{1}{2} \Big(\big(\text{tr}(\boldsymbol{\Phi})\big)^2 - \text{tr}(\boldsymbol{\Phi}^2) \Big) &= \|\mathbf{y}_i\|^2 \|\mathbf{y}_j\|^2 \\ - |\mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_j)^H \mathbf{y}_j|^2, \end{aligned} \tag{21}$$

which can be further summarized as

$$\begin{cases} \lambda_1 + \lambda_2 = \|\mathbf{y}_i\|^2 + \|\mathbf{y}_j\|^2, \\ \lambda_1 \lambda_2 = \|\mathbf{y}_i\|^2 \|\mathbf{y}_j\|^2 - |\mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_j)^H \mathbf{y}_j|^2. \end{cases} \tag{22}$$

Thus, λ_1 and λ_2 are the roots of a quadratic equation:

$$\begin{aligned} &\lambda^2 - (\|\mathbf{y}_i\|^2 + \|\mathbf{y}_j\|^2)\lambda + \|\mathbf{y}_i\|^2 \|\mathbf{y}_j\|^2 \\ &- |\mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_j)^H \mathbf{y}_j|^2 = 0, \end{aligned} \tag{23}$$

and its discriminant is given by

$$\Delta = \big(\|\mathbf{y}_i\|^2 - \|\mathbf{y}_j\|^2\big)^2 + 4|\mathbf{y}_i^H \mathbf{A}(f_i) \mathbf{A}(f_j)^H \mathbf{y}_j|^2 \geq 0. \tag{24}$$

Finally, the largest eigenvalue of $\mathbf{\Phi}$ is given by

$$\lambda_{\max}(\mathbf{\Phi}) = \frac{\|\mathbf{y}_i\|^2 + \|\mathbf{y}_j\|^2 + \sqrt{\Delta}}{2}. \tag{25}$$

Note that only the cross-term $|\mathbf{y}_i^H \mathbf{A}(f_i)\mathbf{A}(f_j)^H \mathbf{y}_j|^2$ in the Δ function is related to the unknown parameters $\{f_i,\ f_j\}$. Substituting (25) back into (16), the ML estimate of $\{f_i,\ f_j\}$ in (16) can be rewritten as

$$\{\hat{f}_i, \hat{f}_j\} = \arg\max_{f_i, f_j} |\mathbf{y}_i^H \mathbf{A}(f_i)\mathbf{A}(f_j)^H \mathbf{y}_j|, \tag{26}$$

which can be simplified as

$$\{\hat{f}_i, \hat{f}_j\} = \arg\max_{f_i, f_j} |\mathbf{y}_i^H \mathbf{A}(f_i - f_j)\mathbf{y}_j|. \tag{27}$$

We notice that the cost function in (27) has the form of a one-dimensional (1-D) inverse FFT (IFFT):

$$\mathbf{y}_i^H \mathbf{A}(f_i - f_j)\mathbf{y}_j = \frac{1}{N}\sum_{n=1}^{N} [\mathbf{g}]_n e^{\jmath 2\pi (n-1)(f_i - f_j)}, \tag{28}$$

where

$$\mathbf{g} = N\mathbf{y}_i^* \odot \mathbf{y}_j. \tag{29}$$

To reduce the computation load, we consider the fast FFT-based implementation method in [24] to find the optimum $(\hat{f}_i - \hat{f}_j)$, instead of using the brute force 2-D search method to solve (27). For more details about the 1-D FFT fast implementation please refer to [24, Section III-C]. Thus, the MLE reduces to identifying the peak of the magnitude of the 1-D IFFT of $\mathbf{g}$. An estimate of $f_i - f_j$ can be obtained based on its relationship to the 1-D IFFT grid u:

$$\hat{f}_i - \hat{f}_j = \frac{u-1}{N_{\mathrm{c}}}, \tag{30}$$

where N_{c} is the 1-D IFFT size. After obtaining estimates for the difference of the Doppler frequency, using the definition of f_i in (2), we have the following relationship between the estimates of the target Doppler $\mathbf{f}$ and target velocity $\mathbf{v}$:

$$\hat{f}_i - \hat{f}_j = \frac{T_{\mathrm{s}}}{\lambda}\big(\hat{v}_x(\cos\theta_i - \cos\theta_j) + \hat{v}_y(\sin\theta_i - \sin\theta_j)\big). \tag{31}$$

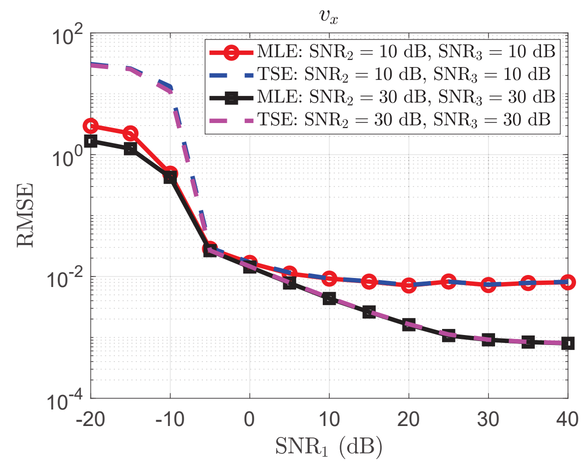
Although there is only one equation for the two unknown variable v_x and v_y, we can use a different group observation (choose from $\mathbf{y}_{\mathrm{A}}$, $\mathbf{y}_{\mathrm{B}}$, and $\mathbf{y}_{\mathrm{C}}$) to obtain another equation, and then jointly solve the two equations for the target velocity, i.e.,

$$\begin{cases} \frac{T_{\mathrm{s}}}{\lambda}\big(\hat{v}_x(\cos\theta_1 - \cos\theta_2) + \hat{v}_y(\sin\theta_1 - \sin\theta_2)\big) = \hat{f}_1 - \hat{f}_2, \\ \frac{T_{\mathrm{s}}}{\lambda}\big(\hat{v}_x(\cos\theta_1 - \cos\theta_3) + \hat{v}_y(\sin\theta_1 - \sin\theta_3)\big) = \hat{f}_1 - \hat{f}_3. \end{cases} \tag{32}$$

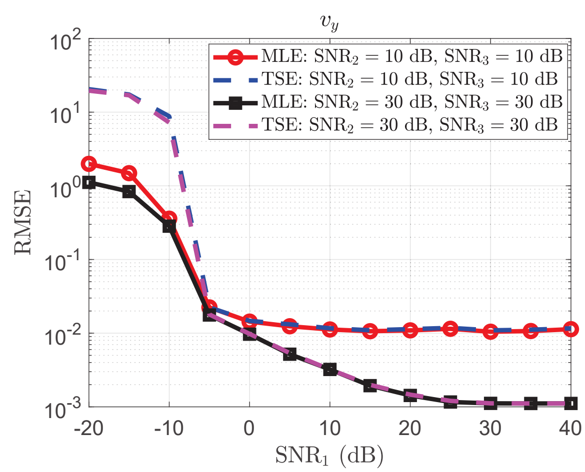
IV. Numerical Simulations

In this section, computer simulations are carried out to demonstrate the performance of the maximum likelihood estimator and the two-step estimator. The SNR at the i-th receiver is defined as $\mathrm{SNR}_i = \frac{NP|\gamma_i|^2}{\sigma_i^2}$, where P is the average power of the transmitted waveform. The distributed sensor network considered here has one transmitted signal source and three receivers. Specifically, the transmitter is located at $\theta_t = 5\pi/4$ and the receivers are located at $\theta_1 = 5\pi/6$, $\theta_2 = 13\pi/8$, and $\theta_3 = \pi/10$, respectively. The other parameters in the simulation are set as follow: the carrier frequency is $f_c = 1$ GHz, the total number of signal samples is $N = 100$, the target velocity is $|\mathbf{v}| = 30$ m/s and the moving direction is $\theta = \pi/3$, the IFFT size for the fast implementation of (28) is $N_{\mathrm{c}} = 1024$, and 500 Monte Carlo trials are carried out to obtain the root-mean-square error (RMSE).

Fig. 2 shows the RMSE for the target velocity v_x and v_y versus SNR_1 with different combinations of SNR_2 and SNR_3, which corresponds to various scenarios for target velocity estimation. It is observed that the RMSE of the computationally efficient TSE is very close to that of the grid search-based MLE for both estimates at high SNR_1 ($\mathrm{SNR}_1 \geq -5$ dB).



(a)



(b)

Fig. 2. RMSEs of the MLE and the TSE versus SNR_1 with different combination of SNR_2 and SNR_3. (a) v_x and (b) v_y.

V. Conclusions

In this paper, we have examined the target velocity estimation problem for a distributed sensor network by treating the transmitted waveform as a deterministic process. An exact MLE, which requires a multi-dimensional search procedure, has been developed. To address the computational burden of the MLE, we have introduced an efficient TSE by dividing the observations from different receivers into pairs and obtain the ML estimates of frequency differences separately. For each pair of observation, the ML estimate can be efficiently obtained with a fast implementation using a 1-D FFT. As a result, the TSE is significantly more efficient than the MLE. Numerical results show that the performance of the computationally efficient TSE is similar to that of the grid search-based MLE.

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