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Distributed ADMM for Target Localization using Radar Networks

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***Abstract*—Traditional target tracking using monostatic radar systems typically rely on centralized or decentralized architectures, where all data is transmitted to a fusion center for estimating the position and velocity of mobile agents. This approach introduces a single point of failure and can significantly increase communication costs, particularly when the fusion center is far from individual radar nodes. To overcome these issues, we introduce a distributed Alternating Direction Method of Multipliers (ADMM) for target localization using a radar network, wherein each radar node shares its observed data only with its immediate neighboring nodes, and achieves consensus with the radar network on the estimated target locations and velocities. We perform simulations incorporating critical system parameters such as the number of radar nodes and Signal-to-Noise Ratio (SNR) to assess their impact of estimation accuracy and convergence speed of the proposed distributed ADMM algorithm. We highlight the additional benefits of our proposed solution, and present directions for future work.**

***Index Terms*—Radar Networks, Maximum Likelihood Estimation, Alternating Direction Method of Multipliers.**

I. Introduction

Radar networks with multiple collaborative nodes are crucial for target detection and tracking in diverse applications [1]. The study of target localization using multiple radar systems is an important research area in radar engineering. These systems are designed for tracking either single [2] or multiple targets [3], and incorporate a variety of configurations such as monostatic [3], bistatic, multistatic [4], [5], MIMO (Multiple-Input and Multiple-Output) [3], and cognitive setups [2]. Despite substantial research on the spatial arrangement of radar nodes and their energy efficiency [6] in target localization scenarios, existing studies predominantly focus on centralized or decentralized data processing.

In a *centralized* framework, raw data, consisting of echo pulses from targets, are transmitted to a single fusion center for processing [5], [7]. Alternatively, in the *decentralized* approach (see Figure 1b), each radar node processes radar data to calculate range and Doppler shift measurements. The nodes then send these measurements to a fusion center to derive a precise localization of the target [4], [5], [8], [9]. In

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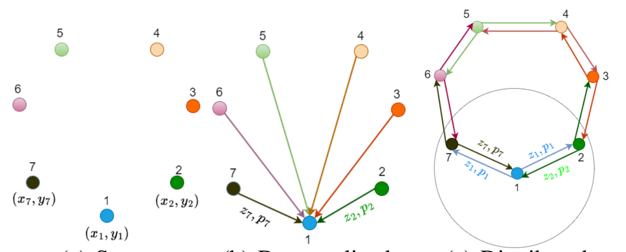


(a) Setup (b) Decentralized (c) Distributed

Fig. 1: An illustration of a Radar setup and data transfer for $N = 7$ nodes in decentralized and distributed frameworks.

both centralized and decentralized radar network frameworks, the reliance on a central fusion center for final data estimates introduces vulnerabilities, such as a single point of failure, and can lead to increased latency particularly if the fusion center is far from the nodes. To overcome these challenges, we propose the use of a distributed optimization algorithms, which have been extensively studied over the past decades [10], [11], which allow for scalability and avoid single point of failure. Among the numerous distributed approaches, such as proximal methods, gossip algorithms, and the method of multipliers, we focus our attention on the Alternating Direction Method of Multipliers (ADMM) [12], [13].

In this paper, we introduce a distributed framework for target localization in radar networks using ADMM, which to the best of our knowledge has not been investigated before. With this, the nodes share range and Doppler measurements only with their nearest neighbors as shown in Figure 1c, enabling precise two-dimensional parameter estimation and reducing single-point failure risks and long-distance communications.

II. Data Model

We consider a network of N omnidirectional monostatic radar nodes, where the nth radar node is located at $\mathbf{p}_n = [x_n, y_n]^T \ \forall n = 1, 2, \ldots, N$. Radar nodes transmit Linear Frequency Modulated (LFM) signals defined by Bandwidth (B) and Wavelength (λ) sending L pulses in each burst—where a burst is a series of pulses sent together to enhance signal accuracy—within a Coherent Processing Interval (CPI). The total targeting time before data transmission for estimation is $M \times$ CPI, with M indicating the number of bursts, each providing M range and Doppler shift measurements.

A. Signal Model

Following a transmission, each radar node in the network receives a noisy, time-delayed and Doppler-shifted version of the transmitted signal. This received signal depends on the geometry of the radar network, and the target position and velocity w.r.t. the corresponding radar node. For the sake of simplicity, we bypass the raw radar data generation and estimation of Doppler shift via Fast Fourier Transform (FFT) during a CPI [14], assumed to be applicable at high SNR scenarios [15]. The noise variance, related to the SNR, is discussed here, whereas details on the measurement model for the nth radar are in Section II-B. The lower bound for range measurement (σ_n^2) can be found using a LFM waveform with a rectangular envelope and a known range rate, and the lower bound on frequency estimation (ρ_n^2) can be calculated, considering a signal model with L pulses and assuming that both the initial phase and amplitude are unknown. The expressions of these variances are given from [14] as

$$\sigma_n^2 \geq \frac{3c^2}{8\pi^2 B_n^2 \mathrm{SNR}_n} \tag{1a}$$

$$\rho_n^2 \geq \frac{3}{2\pi^2 T^2 L(L^2-1)\mathrm{SNR}_n} \approx \frac{3}{2\pi^2 T^2 L^3 \mathrm{SNR}_n} \tag{1b}$$

$$\gamma_{n,m} = \eta \sigma_{n,m} \rho_{n,m} \tag{1c}$$

where the approximation of ρ_n^2 holds for large L, and the covariance between range and Doppler shift is $\gamma_{n,m}$ where, η is the correlation coefficient between the range and Doppler shift measurements.

B. Measurement Model

Let the state parameters of an unknown target be given by $\boldsymbol{\theta} = [\mathbf{p}^T, \mathbf{v}^T]$ where $\mathbf{p} = [x, y]^T$ and $\mathbf{v} = [\dot{x}, \dot{y}]^T$ are the position and velocity of the target in a 2D Cartesian plane. Then the true range and Doppler shift measurements at the nth radar node $\forall n = 1, 2, \ldots, N$ are given by

$$r_n(\boldsymbol{\theta}) = \sqrt{(x_n - x)^2 + (y_n - y)^2} \tag{2}$$

$$f_n(\boldsymbol{\theta}) = \frac{\mathbf{v}^T}{\lambda} \frac{(\mathbf{p}_n - \mathbf{p})}{|\mathbf{p}_n - \mathbf{p}|} \tag{3}$$

where $\frac{(\mathbf{p}_n - \mathbf{p})}{|\mathbf{p}_n - \mathbf{p}|}$ represents the unit vector pointing from the nth radar node to the target, indicating the direction of the relative velocity between the nth radar node and the target. The range and Doppler estimates for M measurements at nth radar node are as follows

$$\begin{bmatrix} \hat{r}_{n,1} \\ \hat{f}_{n,1} \\ \vdots \\ \hat{r}_{n,M} \\ \hat{f}_{n,M} \end{bmatrix} = \begin{bmatrix} r_{n,1}(\boldsymbol{\theta}) \\ f_{n,1}(\boldsymbol{\theta}) \\ \vdots \\ r_{n,M}(\boldsymbol{\theta}) \\ f_{n,M}(\boldsymbol{\theta}) \end{bmatrix} + \begin{bmatrix} e_{rn,1} \\ e_{fn,1} \\ \vdots \\ e_{rn,M} \\ e_{fn,M} \end{bmatrix} \tag{4}$$

where $\hat{r}_{n,m}$ and $\hat{f}_{n,m}$ are the range and Doppler shift measurements at the nth node and mth measurement, and $e_{rn,m}$ and $e_{fn,m}$ are the measurement errors for range and Doppler shift of the mth measurement at the nth node . These measurements depend on the target's characteristics, denoted by $\boldsymbol{\theta}$, and the layout of the radar network. The M measurements from the nth radar node in the network can be combined as

$$\mathbf{z}_n = \boldsymbol{\mu}_n(\boldsymbol{\theta}) + \mathbf{e}_n \tag{5}$$

where $\boldsymbol{\mu}_n(\boldsymbol{\theta})$ is the noiseless true range and Doppler shift measurements of the nth radar node, and $\mathbf{e}_n$ is the underlying zero-mean Gaussian noise on the measurements of the nth radar node with a covariance matrix $\boldsymbol{\Sigma}_\mathbf{n}$, defined as

$$\boldsymbol{\Sigma}_n = \mathrm{blkdiag}(\boldsymbol{\Sigma}_{n,1}, \boldsymbol{\Sigma}_{n,2}, \ldots, \boldsymbol{\Sigma}_{n,M}) \tag{6}$$

$$\boldsymbol{\Sigma}_{\mathbf{n},\mathbf{m}} = \begin{bmatrix} \sigma_{n,m}^2 & \gamma_{n,m} \\ \gamma_{n,m} & \rho_{n,m}^2 \end{bmatrix} \tag{7}$$

where the coefficients of $\boldsymbol{\Sigma}_{n,m}$ are given in (1), and the matrix is symmetric and Positive Semi-Definite (PSD). It is assumed that errors in range and Doppler variables are correlated, and that they follow a multivariate normal distribution with zero mean, where each sample exhibits a correlated pair of errors [4] [5]. Given the properties of the our radar network, to localize the target in 2D space, triangulation is required, necessitating at least three radar nodes [16].

III. Algorithms

A. MLE for Decentralized framework

The measurement model (5) is inherently non-convex, however typically solved commonly using Maximum Likelihood Estimation (MLE) to yield the true solution in high SNR conditions [8], [17]. To estimate the parameters $\boldsymbol{\theta}$, the maximum likelihood estimator is given by

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \Big[-\ln[p(\mathbf{z}; \boldsymbol{\theta})] \Big] \tag{9}$$

where $\ln[p(\mathbf{z}; \boldsymbol{\theta})] = \sum_{n=1}^{N} l_n(\boldsymbol{\theta})$ is the log-likelihood function and $l_n(\boldsymbol{\theta}) = [\mathbf{z}_n - \boldsymbol{\mu}_n(\boldsymbol{\theta})]^T \boldsymbol{\Sigma}_n^{-1} [\mathbf{z}_n - \boldsymbol{\mu}_n(\boldsymbol{\theta})]$. In a traditional decentralized approach, a central node uses MLE to determine the target's position and velocity from range and Doppler data, creating a single point of failure. In this work, we overcome this challenge with a distributed solution.

B. MLE for Distributed framework

Communication links among radar nodes are represented in a fully connected and undirected graph. The neighbors of the nth node are denoted by $j \in \mathcal{N}_n$, where $|\mathcal{N}_n| > 1$ due to the requirements of triangulation. The loglikelihood for the nth radar node is given as

$$\ln[p_n(\mathbf{Z}_n; \boldsymbol{\theta}_n)] = l_n(\boldsymbol{\theta}_n) + \sum_{j \in \mathcal{N}_n} l_j(\boldsymbol{\theta}_n) \tag{10}$$

where $\mathbf{Z}_n$ contains measurements of the nth radar node and those of its neighboring nodes i.e., $\mathbf{Z}_n = \{\mathbf{z}_n\} \cup \{\mathbf{z}_j \mid j \in \mathcal{N}_n\}$ and $\boldsymbol{\theta}_n$ represents the parameters estimated locally at the nth

$$\boldsymbol{\theta}_n(k+1) = \underset{\boldsymbol{\theta}_n}{\operatorname{argmin}} \left[-\ln\left[p_n\left(\mathbf{Z}_n;\boldsymbol{\theta}_n\right)\right] + \sum_{j\in\mathcal{N}_n} \left[\boldsymbol{\psi}_{nj}^T(k)\left(\boldsymbol{\theta}_n - \boldsymbol{\vartheta}_{nj}(k)\right) + \left\| \frac{\boldsymbol{\Phi}}{2}\left(\boldsymbol{\theta}_n - \boldsymbol{\vartheta}_{nj}(k)\right) \right\|_2^2 \right] \right] \tag{8a}$$

$$\boldsymbol{\vartheta}_{nj}(k+1) = \frac{1}{2}\left[\boldsymbol{\Phi}^{-1}\left(\boldsymbol{\psi}_{nj}(k) + \boldsymbol{\psi}_{jn}(k)\right) + \boldsymbol{\theta}_n(k+1) + \boldsymbol{\theta}_j(k+1)\right] \tag{8b}$$

$$\boldsymbol{\psi}_{nj}(k+1) = \boldsymbol{\psi}_{nj}(k) + \boldsymbol{\Phi}\left[\boldsymbol{\theta}_n(k+1) - \boldsymbol{\vartheta}_{nj}(k+1)\right] \tag{8c}$$

node. In contrast to a decentralized solution which relies on a fusion center, we now use an edge variable $\boldsymbol{\vartheta}_{nj}$ to ensure agreement between the nth and jth nodes. This edge-based approach updates the consensus variable locally at each node, eliminating the need for data transmission to a central hub. The updated objective function is given as

$$\begin{aligned} \widehat{\boldsymbol{\theta}}_n = \arg\min_{\boldsymbol{\theta}_n} & \Big[-\ln[p_n(\mathbf{Z}_n;\boldsymbol{\theta}_n)] \Big] \\ \text{s.t.} \quad & \boldsymbol{\theta}_n = \boldsymbol{\vartheta}_{nj}, \quad \boldsymbol{\theta}_j = \boldsymbol{\vartheta}_{nj} \quad \forall j \in \mathcal{N}_n \end{aligned} \tag{11}$$

which can be addressed using a Distributed ADMM (DADMM) algorithm, as outlined in (4) from [13], where the update equations are given in (8a - 8c), where k is the update iteration number, and $\boldsymbol{\Phi}$ is the diagonal penalty matrix with different penalties for position and velocity, accounting for their distinct sensitivities and physical characteristics. Different penalties are needed because position (in $'m'$) and velocity (in $'m/s'$) affect system behavior differently and have different units, magnitudes, and error scales. Here, the dual variables $\boldsymbol{\psi}_{nj}$ and $\boldsymbol{\psi}_{jn}$ are adjusted by the penalty matrix $\boldsymbol{\Phi}$ to reflect deviations in achieving consensus from previous iterations. These adjustments are incorporated into the averaging process, modifying $\boldsymbol{\vartheta}_{nj}$ to address past discrepancies, thus promoting stable and effective convergence towards consensus. Although the underlying cost function is non-convex, ADMM leverages local convexity from a PSD Hessian, enhancing convergence toward a local minimum. Furthermore, employing higher penalty terms on the Augumented lagrangian improves ADMM's effectiveness with non-convex functions [18]. We check convergence via the primal residual in (12) which shows discrepancies between local estimates $\boldsymbol{\theta}_n$ and the consensus, assessing the ADMM algorithm's effectiveness in meeting constraints and reaching an optimal solution.

$$r_n(k+1) = \sqrt{\sum_{j\in\mathcal{N}_n} \left\|\boldsymbol{\theta}_{\mathbf{n}}(\mathbf{k+1}) - \boldsymbol{\vartheta}_{\mathbf{nj}}(\mathbf{k+1})\right\|_2^2} \tag{12}$$

The proposed algorithm for DADMM for target localization at the nth radar node is summarized in Algorithm 1.

Algorithm 1: DADMM for Localization (nth node)

Input: Initialize $\boldsymbol{\psi}_{nj}(0)$, $\boldsymbol{\theta}_n(0)$ and $\boldsymbol{\vartheta}_{nj}(0)$ randomly $j \in \mathcal{N}_n$, Define $\boldsymbol{\Phi}$ based on SNR and set $k = 0$;

while $(r_n(k+1) > \epsilon^{pri})$ **do**
- Update $\boldsymbol{\theta}_n(k+1)$ using (8a);
- Transmit $\boldsymbol{\psi}_{nj}(k)$ to all neighbors $j \in \mathcal{N}_n$;
- Transmit $\boldsymbol{\theta}_n(k+1)$ to neighbors $j \in \mathcal{N}_n$;
- Update $\boldsymbol{\vartheta}_{nj}(k+1)$ using $(8b)$;
- Transmit $\boldsymbol{\vartheta}_{nj}(k+1)$ to neighbors $j \in \mathcal{N}_n$;
- Update $\{\boldsymbol{\psi}_{nj}(k+1)\}_{j\in\mathcal{N}_n}$ using (8c);
- Increment k;

end

Output: $\hat{\theta}_n$

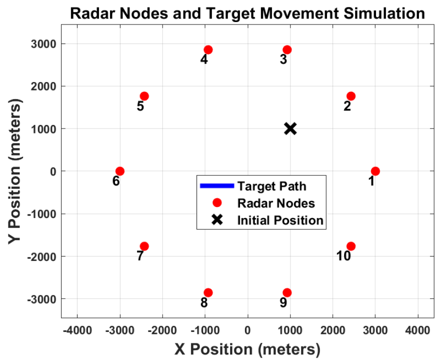
IV. Simulation Results

Simulations are performed to evaluate the proposed decentralized and distributed approaches. Radar nodes are deployed in a uniform circular geometry with a 3 km radius, removing directional bias and ensuring symmetric communication in a distributed approach. The target starts at $\mathbf{p} = [1000, 1000]^T$ m, moving at a constant speed of 20 m/s at a $135°$ angle, as shown in Figure 2. Each radar transmits an LFM signal with B=10MHz, L=32, λ=0.03m, and estimates 32 measurements (M) before sending these measurements to estimate $\boldsymbol{\theta}$. Given this simulation setup, we evaluate the performance of the centralized MLE (9) for different number of radar nodes, and plot the standard deviation of our position and velocity estimates and the corresponding Root CRLB [5], [8]. The results are presented in Figures 3a - 3d, where we show that the performance of the MLE is consistent with the theoretical lower bounds, for lower SNR.

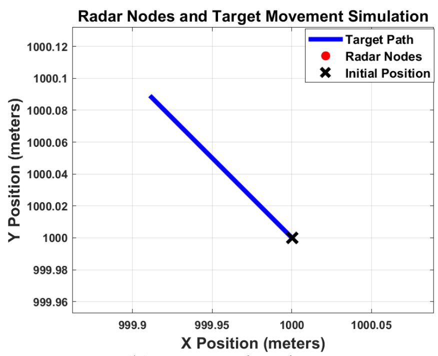
To evaluate our proposed DADMM algorithm, we deploy $N = 10$ radar nodes, as shown in Figure 2a, where each node has a communication radius of 3km and the communication graph between the nodes are modeled as Unit Disc Graphs (UDG) [11], [19], [20]. We adjust the penalty terms within the penalty matrix for position and velocity parameters based on SNR i.e., higher penalties are applied at lower SNRs to address increased uncertainty, while lower penalties suffice at higher SNRs, reflecting the reduced uncertainty. Figures 3e - 3h demonstrate to achieve consensus within limited iterations, and in particular the position estimates converge faster than velocity estimates, as these are influenced by the target's radial velocity and directional orientation relative to each radar. On the contrary, the velocity estimates generally require more iterations to converge, hence different stopping criteria can be employed for these parameters.

V. Conclusion

In this paper, we presented a Distributed ADMM approach for target localization using radar networks. Our method differs from traditional radar systems, which rely on centralized



(a) Radar Geometry



(b) Target Direction

Fig. 2: N=10 radars deployed in a circle, with the target moving at 135° w.r.t. the x-axis.

or decentralized architectures vulnerable to single points of failure and extended data transmission times, by enabling each radar node to share observed data exclusively with its nearest neighbors, thus facilitating local estimation of target position and velocity while achieving network-wide consensus. We conducted simulations to assess how variations in the number of radar nodes and SNR impact the uncertainty in target estimation, and demonstrated how our distributed ADMM method effectively removes the single point of failure and converts to true values at high SNRs.

This distributed approach could notably reduce power consumption and improve data throughput efficiency, beneficial for sectors like Aerial Vehicles [21] and Urban Traffic Monitoring and Control [22]. Adjusting the stopping criteria for the primal residual (ϵ^{pri}) allows for a fine-tuned balance between accuracy and computational efficiency. A lower stopping threshold ensures greater precision through more iterations, while optimal initial parameter settings may speed up the convergence of the estimated parameters ($\hat{\boldsymbol{\theta}}$), potentially reducing iteration counts and enhancing energy efficiency.

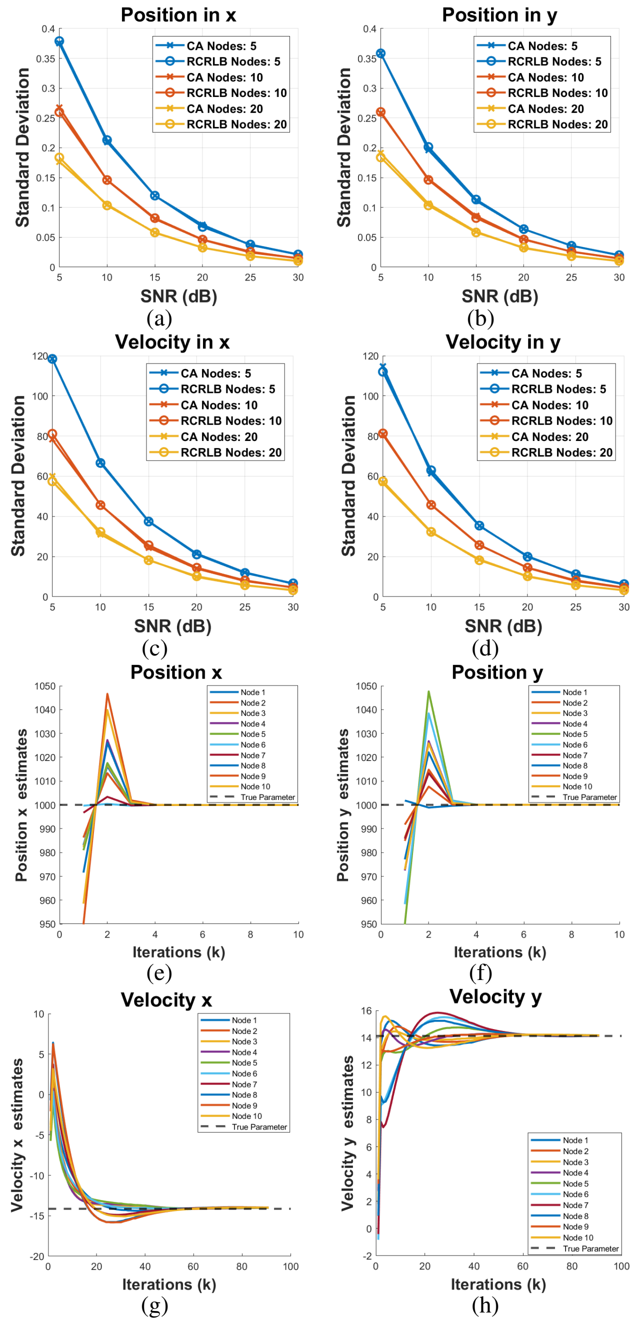


Fig. 3: The plots (a) - (d) show the standard deviation of the estimated $\hat{\theta}$ for different number of radar nodes N of 5, 10, and 20, for varying SNR levels [8]; The plots (e) - (h) demonstrate the consensus achieved by N=10 radar nodes at 30dB SNR.

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