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Dynamic Nodes Based Cooperative Positioning of D2D Systems in GNSS-Denied Environments

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Abstract—This letter presents a novel mobility-aware device-to-device (D2D) cooperative positioning scheme for dynamic nodes. We employ the Gauss-Markov mobility model to represent and simulate the movement of mobile nodes. Initially, we create a Euclidean distance tensor (EDT) by combining Euclidean distance matrices (EDMs) collected at various time stamps. The nonline of sight (NLoS) conditions in global navigation satellite system (GNSS)-Denied environments lead to missing data in EDM which results in inaccurate positioning of D2D nodes. To address this issue, we utilize the high accuracy low rank tensor completion (HaLRTC) algorithm to effectively fill in the missing entries within the EDMs for each time stamp. Subsequently, we utilize multidimensional scaling (MDS) to derive the relative positions of the nodes. While the locations of the anchor nodes remain fixed, we employ Procrustes analysis (PA) to determine the global positions of the unknown nodes. Simulation results demonstrate that our proposed approach achieves a localization error of 0.2017 m with a sparsity level of 90%, along with a ranging error rate of 20%, thus offering high accuracy.

Index Terms—Sensor signal processing, cooperative positioning, device-to-device (D2D), Euclidean distance tensor (EDT), Gauss-Markov mobility model, high accuracy low rank tensor completion (HaLRTC).

I. INTRODUCTION

With the emergence of fifth-generation (5G) and beyond 5G (B5G), device-to-device (D2D) communication has become a crucial technology offering several advantages, including enhanced spectral efficiency, improved security, reduced latency, and broader coverage. In this context, high-accuracy positioning plays a vital role in traditional location-based services, enabling enhanced communication efficiency and facilitating the integration of new applications that require exceptional performance [1].

Powered by the advantages of D2D communication, cooperative D2D positioning can prove helpful in instances where global navigation satellite system (GNSS) signals are not accessible, especially indoors. In recent years, a significant amount of research has gone into the field of D2D positioning with the rise of 5G and next-generation technology. To solve the synchronization and timing issue between the devices in the time of arrival (TOA) positioning algorithm, the two way time of arrival (TW-TOA) ranging protocol was proposed in [2] for D2D positioning. Khandker et al. [3] introduced a collaborative method based on D2D communication for enhancing the positioning accuracy. Yin et al. [4] proposed a GNSS/5G integrated positioning scheme that utilized D2D communication and crossover multiple-way ranging. Zhang et al. [5] proposed a new centralized D2D co-location algorithm that employs density-based spatial clustering of applications with noise clustering. Building upon the aforementioned study, Zhang et al. [6] introduced a 3-D positioning method that integrates GNSS and 5G technology which is suitable for both fixed and dynamic scenarios.

Wu et al. [7] presented a mobile positioning approach that uses recurrent neural networks. However, this letter does not specifically address the issue of mitigating data loss. Zhou et al. [8] addressed the positioning issue in a static D2D with insufficient distance information and suggested a D2D cooperative positioning that incorporates matrix completion through singular value thresholding (SVT) algorithm, along with anchor selection employing the Hodges-Lehmann (HL) test. However, the abovementioned algorithm is yet to be tested in a mobile environment. In real-time scenarios, the devices are not fixed; instead, they are mobile. Destiarti et al. [9] proposed a mobile cooperative tracking based on extended RSSI ranging to continuously obtain localization information from the three nearest reference devices, and the positioning error was effectively reduced by employing the extended Kalman filter (EKF). The cooperative localization of mobile networks utilizing the relative velocity measurements was addressed in [10] and [11]. However, these existing studies have limitations as they fail to account for nonline-of-sight (NLoS) propagation, absence of relative velocity measurements, challenging environments, and limitations in practical systems involving mobile nodes. This letter proposes a novel mobility-aware D2D cooperative positioning scheme in GNSS denied environment that takes into account the limitations of

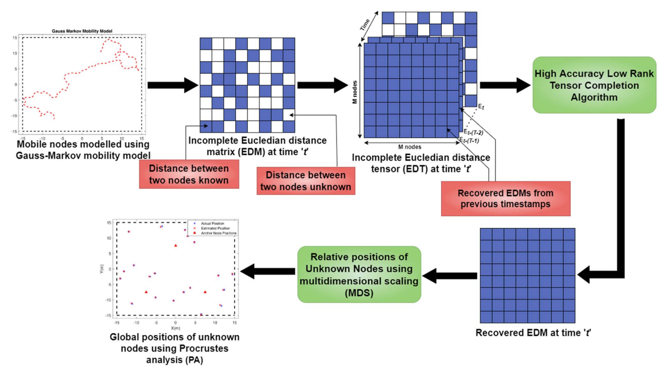

Fig. 1. Work flow.

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previous research, leveraging temporal dependencies and adopting a realistic Gauss-Markov mobility (GMM) model. The main contributions of this letter are listed below as follows.

1) We introduce the GMM model to simulate the movement of mobile nodes and analyze the proposed D2D positioning algorithm.
2) We address the issue of incomplete Euclidean distance matrices (EDMs) arising from NLoS occurring in GNSS-denied environments. We propose an algorithm based on high accuracy low rank tensor completion (HaLRTC), which effectively recovers the missing entries in the incomplete EDM.
3) The tensor formulation combines the incomplete EDM at the current time stamp with the previously obtained complete EDM. This memory feature enables the EDT to capture the temporal dynamics of mobile node movements and increase accuracy by exploiting the correlations between consecutive time stamps.
4) We evaluate the performance of the proposed algorithm using the suggested mobility model and measure its accuracy.

II. SYSTEM MODEL

We consider a mobile environment consisting of a total of M nodes, including N unknown nodes and three fixed anchor nodes equipped with D2D capabilities. The precise global positions of the anchor nodes are assumed to be accurately known. Our primary objective is to estimate the real-time positions of the N unknown nodes. The distances between nodes, including both the unknown and anchor nodes, can be estimated using various methods such as time of arrival (TOA), received signal strength (RSS), and round trip time (RTT). We assume that the distance data is updated at a refresh rate of R Hz. However, due to factors such as NLoS environments and other considerations, the obtained distance data is inherently incomplete. Hence, in order to address this challenge within a mobile environment, we require an algorithm capable of accurately estimating the missing distance information, while being specifically tailored for such dynamic scenarios. The flow diagram of the proposed approach is illustrated in Fig. 1. This method utilizes a GMM model to simulate the movement of mobile nodes and then constructs an incomplete EDM at each time stamp. It employs the high accuracy low rank tensor completion algorithm to recover the EDM, followed by determining the relative and global positions of unknown nodes.

A. Mobility Model

We employ a GMM model that accurately simulates the movement of mobile nodes to evaluate the performance of the proposed D2D positioning scheme. Through the comparison of predicted positions obtained using the proposed algorithm with the actual positions derived from the mobility model, we can assess the accuracy of the algorithm. The GMM model [12], [13], and [14] assumes that the mobility patterns of nodes are influenced by their previous locations and velocities. The memory feature of GMM model aligns well with real-world mobility patterns, as people or vehicles often exhibit correlated movement over time. The speed and direction at time t, $v(t)$, and $\theta(t)$ based on the speed and direction at time $t-1$, $v(t-1)$ and $\theta(t-1)$ are given by

$$v(t) = \alpha v(t-1) + (1-\alpha)\overline{v} + \sqrt{(1-\alpha^2)}v_g(t-1) \quad (1)$$

$$\theta(t) = \alpha \theta(t-1) + (1-\alpha)\overline{\theta} + \sqrt{(1-\alpha^2)}\theta_g(t-1) \quad (2)$$

where $\overline{v}$ and $\overline{\theta}$ represent the average speed and average direction, respectively; v_g and θ_g follow Gaussian distributions; and the tuning parameter for random variation is given by $0 \le \alpha \le 1$. The new position of the node at time t, $(x(t), y(t))$ is calculated as follows:

TABLE 1. Parameter Settings

Parameters	Values
Area of simulation environment	30×30 m^2
Total number of nodes	23
Number of anchor nodes	3
Number of unknown nodes	20
Global positions of anchor nodes	[(0, 7.5),(−7.5, −7.5),(7.5, −7.5)]
Velocity range	1–2 m/s
Refresh rate	1 Hz
Maximum iterations in HaLRTC	800
Size of EDT	$23 \times 23 \times 2$

$$x(t) = x(t-1) + v(t-1) \times \cos(\theta(t-1)) \quad (3)$$

$$y(t) = y(t-1) + v(t-1) \times \sin(\theta(t-1)). \quad (4)$$

III. SYSTEM DESCRIPTION

The distances obtained through TOA or RSS measurements are organized into an EDM. However, the EDM is prone to incompleteness due to NLoS conditions between the nodes.

A. Tensor Formulation

In a real environment, EDM is likely to be incomplete. To address this, we propose formulating a Eucledian distance tensor (EDT) that incorporates the incomplete EDM at time t along with the previously recovered complete EDMs. The EDT is iteratively formulated at each time stamp, and the completion of the EDM is achieved by leveraging the previously recovered EDMs.

For a refresh rate of R Hz, the time gap between two consecutive time stamps t will be

$$t = \frac{1}{R}. \quad (5)$$

Consider $\mathbf{E}_t$ as the incomplete EDM at time t, and $\mathbf{E}_{t-1}$, $\mathbf{E}_{t-2}$, ..., $\mathbf{E}_{t-(T-1)}$ as the recovered complete EDMs at time stamps $t-1$, $t-2, \ldots, t-(T-1)$, respectively. Let $\mathbf{E}_t, \mathbf{E}_{t-1}, \mathbf{E}_{t-2}, \ldots, \mathbf{E}_{t-(T-1)} \in \mathbb{R}^{M\times M}$. The formulated tensor denoted as $\mathcal{T} \in R^{M\times M\times T}$ is defined as

$$\mathcal{T}_{:,:,1} = \mathbf{E}_{t-(T-1)} \quad (6)$$

$$\mathcal{T}_{:,:,2} = \mathbf{E}_{t-(T-2)} \quad (7)$$

$$\vdots$$

$$\mathcal{T}_{:,:,T} = \mathbf{E}_t. \quad (8)$$

The visual representation for the structure of the formulated tensor, $\mathcal{T}$ is shown in Fig. 1.

B. Tensor Completion

The completion of the incomplete EDT can be achieved using HaLRTC [15]. The tensor completion problem can be formulated as follows:

$$\begin{aligned} \min_{\mathcal{X},\mathbf{E}_1,\ldots,\mathbf{E}_n} &: \sum_{i=1}^{n} \alpha_i ||\mathbf{E}_{i(i)}||_* \\ \text{s.t.} &: \mathcal{X}_\Omega = \mathcal{T}_\Omega \\ \mathcal{X} &= \mathbf{E}_i, \qquad i = 1, \ldots, n. \end{aligned} \quad (9)$$

Algorithm 1: High Accuracy Low Rank Tensor Completion.

```
Input: 𝒳 with 𝒳_Ω = 𝒯_Ω, δ and total number of iterations, J
Output: 𝒳
Set 𝒳_Ω = 𝒯_Ω and 𝒳_Ω̄ = 0.
for j = 0 to J do
  for i = 1 to n do
    E_i = fold_i[D_{α_i/δ}(𝒳_(i) + (1/δ) γ_i(i))]
  end for
  𝒳_Ω = (1/n)(Σ_{i=1}^n E_i − (1/δ) γ_i(i))_Ω̄
  γ_i = γ_i − δ(E_i − 𝒳)
end for
```

Algorithm 2: Proposed Algorithm.

Input: Complete EDMs ($\mathbf{E}_{t-1}, \ldots, \mathbf{E}_{t-(T-1)}$), incomplete EDM($\mathbf{E}_t$), global positions of 3 anchor nodes, total time T_{tot}
Output: Global positions of N unknown nodes

while $t \leq T_{tot}$ **do**
  Formulate the EDT,

$$\mathcal{T} = [\mathbf{E}_{t-(T-1)}, \mathbf{E}_{t-(T-2)}, \ldots, \mathbf{E}_t]$$

  Apply HaLRTC on $\mathcal{T}$ to obtain complete EDT.
  Obtain the relative positions of M nodes using MDS
  Obtain the global positions of N nodes with the help of PA, using the global position of 3 anchor nodes.
end while

The augmented Lagrangian function is defined as $L_p(\mathcal{X}, \mathbf{E}_1, \ldots, \mathbf{E}_n, \gamma_1, \ldots, \gamma_n)$

$$= \sum_{i=1}^{n} \alpha_i ||\mathbf{E}_{i(i)}||_* + \langle \mathcal{X} - \mathbf{E}_i, \gamma_i \rangle + \frac{\delta}{2} ||\mathbf{E}_i - \mathcal{X}||_F^2. \quad (10)$$

In (10), we incorporate an iterative parameter δ, which is updated at each iteration such that $\delta^{j+1} = k\delta^j$ for accelerating the algorithm. The steps involved in HaLRTC are outlined in Algorithm 1.

C. Global Positioning of Unknown Nodes

After obtaining the complete EDM, the global positions of the unknown nodes are determined. We have employed multidimensional scaling (MDS) to derive the relative positions of the nodes. Subsequently, utilizing the known global positions of the anchor nodes, we apply Procrustes analysis (PA) [8] to compute the global positions of the unknown nodes. PA was chosen due to its compatibility with the relative positions derived from MDS.

IV. PERFORMANCE EVALUATION

A. Simulation Configuration

For the simulation, a total of 23 nodes are deployed, comprising 20 unknown nodes and three fixed anchor nodes. The deployment area spans 30 × 30 m^2. The mobile nodes are modeled using the GMM model, with velocities ranging from 1 to 2 m/s. The chosen speed range is suitable for indoor positioning applications, particularly for monitoring human movement. The distance data is sampled at a refresh rate of 1 Hz [16]. The measurement errors are accounted for by introducing the ranging error rate denoted as ER as in [8]. The measured distance between nodes, $d_{i,j}$ is uniformly distributed as $d_{i,j}[1 + U(-ER, ER)]$, where $U(-ER, ER)$ represents a uniform distribution between $-ER$ and ER.

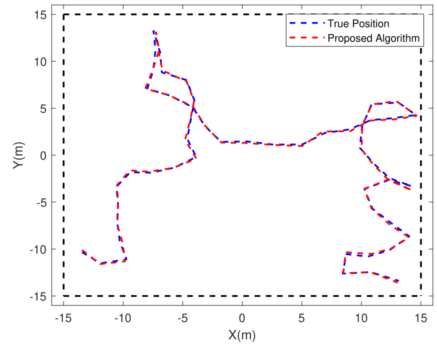

Fig. 2. Live positioning of a single node.

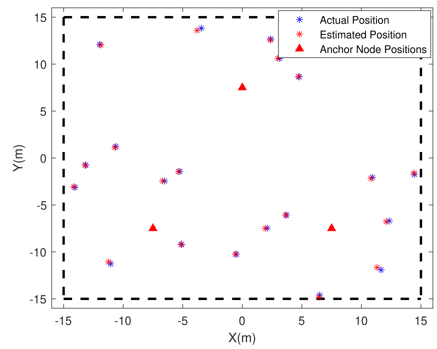

Fig. 3. Estimated versus global position of mobile nodes.

The sparsity level (P_s) of the incomplete EDM represents the percentage of missing elements in the matrix [8]. The initial EDM elements are defined based on the distances between the initial positions of the nodes in the simulated environment. A randomized method is used to determine the positions of the missing elements in the EDM. The simulation parameters are shown in Table 1.

B. Simulation Results

The positioning results of a single node over a specific time duration, with a ranging error rate of $ER = 10\%$, and a sparsity level of $P_s = 10\%$ is shown in Fig. 2, displaying both the true position of the node generated by the GMM model and the predicted position of the node obtained through the utilization of the proposed algorithm. A comparison of the estimated and global (actual) positions of the unknown nodes along with positions of anchor nodes is illustrated in Fig. 3. The evaluation is conducted at a specific time stamp. The graph provides a visual depiction of the accuracy of the positioning algorithm, allowing for a clear assessment of the alignment between the estimated and true positions.

Fig. 4 presents a comparison of the cumulative density function (CDF) of positioning errors for different sparsity levels, $P_s = 0\%$, 10%, 20%, 30%, 40%, 50%. The ranging error rate is held constant at $ER = 20\%$. The CDF curves provide insights into the probability distribution of positioning errors, indicating the likelihood of errors falling within certain ranges. Notably, the observed probabilities of positioning errors being within 1 m for each sparsity level are as follows: 100%, 100%, 96.2%, 87.3%, 54.9%, 26.5%. Fig. 5 illustrates the comparison of the CDF of positioning errors for different ranging error rates, $ER = 10\%$, 30%, 50%, 70%. The sparsity level remains

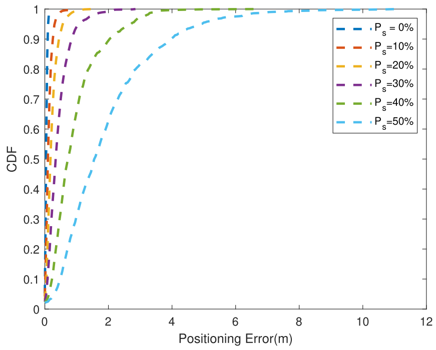

Fig. 4. CDF of Positioning Error for different P_s with $ER = 20\%$.

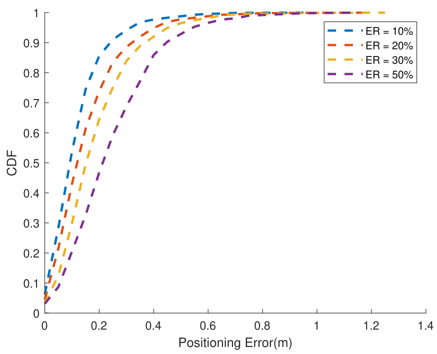

Fig. 5. CDF of Positioning Error for different ER with $P_s = 10\%$.

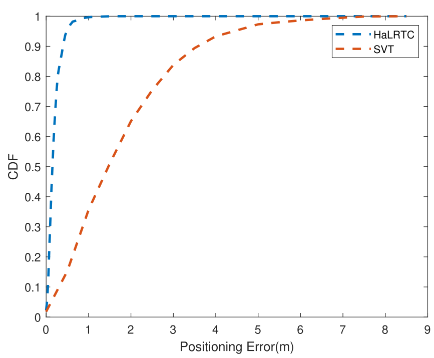

Fig. 6. Comparison of HaLRTC with SVT.

fixed at $P_s = 20\%$. The impact of varying ranging error rates on the distribution of positioning errors and the performance of system under different error conditions are verified by examining the CDF curves.

A comparison between the HaLRTC algorithm employed in this letter and the SVT algorithm used in [8] is shown in Fig. 6. The CDF of positioning error is computed for a ranging error rate (ER) of 10% and a sparsity level (P_s) of 10%. The observed results from the CDF demonstrate that the HaLRTC algorithm delivers superior outcomes. Furthermore, we tested the proposed algorithm using the random waypoint mobility model, and it generated comparable simulation results.

V. CONCLUSION

In this letter, a novel mobility-aware D2D cooperative positioning scheme for dynamic nodes in GNSS denied environment is modelled. The proposed system utilizes a low rank tensor completion algorithm, HaLRTC to recover the incomplete EDM. Subsequently, MDS and PA are applied to determine the global positioning of the unknown nodes. With a sparsity level of 90% and a ranging error rate of 20%, the proposed scheme achieves a remarkable localization error of only 0.2017 m for 20 unknown nodes, demonstrating its high accuracy. The applicability of this algorithm extends to real-time applications such as indoor positioning, augmented reality/virtual reality (AR/VR), and more. Future work may include integrating anchor node selection to enhance the accuracy of the proposed algorithm. Moreover, we can validate the algorithm by developing a test platform in real-world scenarios to assess its precision and performance.

REFERENCES

[1] A. Behravan et al., “Positioning and sensing in 6G: Gaps, challenges, and opportunities,” *IEEE Veh. Technol. Mag.*, vol. 18, no. 1, pp. 40–48, Mar. 2023.
[2] X. Cui, T. A. Gulliver, H. Song, and J. Li, “Real-time positioning based on millimeter wave device to device communications,” *IEEE Access*, vol. 4, pp. 5520–5530, 2016.
[3] S. Khandker, J. Torres-Sospedra, and T. Ristaniemi, “Improving RF fingerprinting methods by means of D2D communication protocol,” *Electronics*, vol. 8, no. 1, 2019, Art. no. 97.
[4] L. Yin, Q. Ni, and Z. Deng, “A GNSS/5G integrated positioning methodology in D2D communication networks,” *IEEE J. Sel. Areas Commun.*, vol. 36, no. 2, pp. 351–362, Feb. 2018.
[5] J. Zhang, F. Yang, Z. Deng, X. Fu, and J. Han, “Research on D2D co-localization algorithm based on clustering filtering,” *China Commun.*, vol. 17, no. 8, pp. 121–132, 2020.
[6] W. Zhang, Y. Yang, A. Zeng, and Y. Xu, “A GNSS/5G integrated three-dimensional positioning scheme based on D2D communication,” *Remote Sens.*, vol. 14, no. 6, 2022, Art. no. 1517.
[7] L. Wu, C.-H. Chen, and Q. Zhang, “A mobile positioning method based on deep learning techniques,” *Electronics*, vol. 8, no. 1, 2019, Art. no. 59.
[8] M. Zhou, Y. Li, Y. Wang, Q. Pu, X. Yang, and W. Nie, “Device-to-device cooperative positioning via matrix completion and anchor selection,” *IEEE Internet Things J.*, vol. 9, no. 7, pp. 5461–5473, Apr. 2022.
[9] A. R. Destiarti, P. Kristalina, and A. Sudarsono, “Mobile cooperative tracking with RSSI ranging in EKF algorithm for indoor wireless sensor network,” in *Proc. IEEE Int. Conf. Knowl. Creation Intell. Comput.*, 2016, pp. 60–66.
[10] S. Kumar, R. Kumar, and K. Rajawat, “Cooperative localization of mobile networks via velocity-assisted multidimensional scaling,” *IEEE Trans. Signal Process.*, vol. 64, no. 7, pp. 1744–1758, Apr. 2016.
[11] Y. Fan, K. Ding, X. Qi, and L. Liu, “Cooperative localization of 3D mobile networks via relative distance and velocity measurement,” *IEEE Commun. Lett.*, vol. 25, no. 9, pp. 2899–2903, Sep. 2021.
[12] M. R. Marani, S. M. Mirrezaei, and R. Mirzavand, “Joint throughput and coverage maximization for moving users by optimum UAV positioning in the presence of underlaid D2D communications,” *AEU- Int. J. Electron. Commun.*, vol. 161, 2023, Art. no. 154541.
[13] P. H. Barros, I. Cardoso-Pereira, L. Foschini, A. Corradi, and H. S. Ramos, “Load balancing in D2D networks using reinforcement learning,” in *Proc. IEEE Symp. Comput. Commun.*, 2019, pp. 1–6.
[14] Z. ZHONG, L. Da-Yong, L. Shao-Qiang, F. Xiao-Ping, and Q. Zhi-Hua, “An adaptive localization approach for wireless sensor networks based on Gauss-Markov mobility model,” *Acta Autom. Sinica*, vol. 36, no. 11, pp. 1557–1568, 2010.
[15] J. Liu, P. Musialski, P. Wonka, and J. Ye, “Tensor completion for estimating missing values in visual data,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 1, pp. 208–220, Jan. 2013.
[16] M. S. Rahman, A. Chakraborty, K. Sunderasan, and S. Rangarajan, “DynoLoc: Infrastructure-free RF tracking in dynamic indoor environments,” 2022.