In: 2022 IEEE Globecom Workshops (GC Wkshps), 4-8 December 2022, Rio de Janeiro, Brazil, pp. 1437-1441
DOI: 10.1109/GCWkshps56602.2022.10008692

Multi-UAV Wireless Positioning using Adaptive Multidimensional Scaling and Extended Kalman Filter

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***Abstract*—Global Navigation Satellite System (GNSS) signal can be blocked when flight vehicles operate in challenging environments such as indoor or adversarial environments. While multi-UAVs are teamed during flight, cooperative localization becomes available to tackle this challenge. Multidimensional Scaling (MDS) method has been well studied for cooperative localization of Wireless Sensor Network (WSN) based on radio frequency (RF) measurement. When noise RF measurement model is lacking, conventional weighted MDS method represents confidence with the measurements by assigning weights relying on distance information between each pair of nodes. In order to process non-distance RF measurements, we present an improved weighted MDS method which applies a novel weighting scheme. In this article, the proposed method conducts velocity estimation for multi-UAV system based on odometry and Frequency Difference of Arrival (FDOA) measurements. Furthermore, an extended Kalman Filter (EKF) algorithm is applied to refine the initial estimation of the MDS method and derive position estimation. Finally, numerical experiments demonstrate the robustness and accuracy of the adaptive MDS-EKF refinement framework for multi-UAV system localization in an unknown dynamic environment lacking measurement noise information.**

***Index Terms*—Cooperative Localization, Wireless Signal, FDOA, Multidimensional Scaling, EKF, Adaptive, GNSS-denied**

I. Introduction

The multi-unmanned aerial vehicle (UAV) system has become very attractive in recent years in terms of its promising military and civil application potentials [1]–[3]. This includes routing data packets in V2V applications [4], as well as providing dynamic coverage in Self-Organising-Networks (SONs) [5]. Part of the challenge is swarm UAV coordination which typically needs Global Navigation Satellite System (GNSS). However, considering that UAVs often operates in the challenging environments, where the GNSS becomes unavailable because of poor signal or interference, a reliable localization system is critical for the multi-UAV system to execute tasks successfully in the GNSS-denied environment [6]. The radio-frequency (RF) based cooperative localization solutions have attracted a growing research attention due to the advantages of low cost, low latency, low power consumption and high precision [7].

Multidimensional scaling (MDS) is a typical cooperative localization method for wireless sensor network (WSN) localization [8]. MDS is a dimensionality reduction method which maps high-dimensional distance matrix of a set of nodes (dimension equals to the number of nodes) to low-dimensional points in 2-D or 3-D space [9]. Considering cooperative localization as non-convex optimization problem, iterative MDS method handles dimensionality reduction through solving the STRESS function as introduced in Section II-B [10]. The current literature studies the application of MDS-based localization method for mobile WSN [11]–[13]. Furthermore, successive refinement frameworks have been proposed which combine MDS with the methods, e.g., Gradient-based approach and Kalman Filter in [14]–[17] in order to achieve improved estimation precision. When there exists noise in the RF measurement environment, the measurement error will degrade the localization performance. Therefore, weighting scheme has been proposed in [18] which represents confidence with each measurement. When the measurement noise model is available, weight for each measurement can be calculated based on the model [18], [19]. However, adaptive weighting scheme is required when the model becomes unavailable in the noise unknown environment [18]. By far, there are only a few literature which have proposed adaptive weighting schemes with certain application limitations.

A. Open Challenges

In [10], [13], [20], the weighting scheme is simplified by setting a unit value to each measurement when the noise measurement model is not available. This causes robustness issue for localization when the measurement error is significant. In [14], instead of defining adaptive weighting

This work was partly supported by the Chevening Scholarships, the UK government's global scholarship programme, funded by the Foreign, Commonwealth and Development Office (FCDO) and partner organisations, and EC H2020 DAWN4IoE - Data Aware Wireless Network for Internet-of-Everything (778305).

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scheme, the distance is estimated based on the mean of noise measurements in history of stationary WSN. In [18], the locally weighted regression (LOESS) method is adopted for the adaptive weighting scheme. Believing that the RF measurement is more accurate when the two nodes have the shorter distance, the LOESS method is used to assign the greater weight to short distance measurement. Nevertheless, this method is not available when the RF measurement is non-distance information, such as velocity or angle. There exists the research gap on developing a weighted MDS method which is universally adaptive to both distance and non-distance RF measurements for mobile WSN.

B. Contribution

Our contribution is to present a novel adaptive weighting scheme which estimates confidence of each measurement without relying on distance. By applying the scheme, the improved weighted MDS method conducts velocity estimation for multi-UAV system based on odometry and FDOA measurements. Subsequently, an adaptive MDS-EKF refinement framework is constructed to further improve the localization estimation accuracy.

II. Adaptive MDS-EKF Refinement Framework

A. Problem Statement

Consider a multi-UAV system constituted with n UAVs in the 3D environment where GNSS signal is blocked, which is denoted as $\mathbf{\Lambda} = \left\{\chi_1 \quad \cdots \quad \chi_n\right\}$. χ_i represents the UAV i. $\chi_i^{(k)}$ describes as the node which represents the UAV i at the MDS estimation-step k. Arrange all the UAV nodes at the estimation-step k in $\mathbf{\Lambda}^{(k)} = \left\{\chi_1^{(k)} \quad \cdots \quad \chi_n^{(k)}\right\}$. Assume the prior knowledge of the initial position and velocity of each UAV is available. The objective is to estimate position of the multi-UAV system $\mathbf{\Lambda}$.

Each UAV is equipped with the same type of sensors, including: accelerometer, altimeter, magnetometer and FDOA measurement sensor. Each of the sensor is assumed to have the measurement noise with Gaussian distribution which is considered as prior knowledge except the FODA measurement. The velocity change of UAV i between the MDS estimation-step $k-1$ and k acquired by the accelerometer is denoted as $\delta_{ii}^{(k)}$. Arrange the velocity change of all the UAVs in the matrix $\mathbf{\Delta}^{(k)} \in \mathbb{R}^{n\times n}$, where $[\mathbf{\Delta}^{(k)}]_{ii} = \delta_{ii}^{(k)}$, and $[\mathbf{\Delta}^{(k)}]_{ij,i\neq j} = 0$. The relative velocity between UAV i and UAV j measured by FDOA measurement sensor at the MDS estimation step k is denoted as $\mu_{ij}^{(k)}$. Arrange the pairwise relative velocity in the matrix $\mathbf{M}^{(k)} \in \mathbb{R}^{n\times n}$, where $[\mathbf{M}^{(k)}]_{ii} = 0$, and $[\mathbf{M}^{(k)}]_{ij,i\neq j} = \mu_{ij}^{(k)}$. The altitude measured by the altimeter is denoted as $h_i^{(k)}$. The heading angle based on magnetometer measurement is denoted as $\theta_i^{(k)}$.

The amount of the UAVs n must be greater than 4 so that there are at least three pairwise relative velocity measurements available for each UAV for the purpose of MDS estimation.

B. Range-Odometry MDS

In this paper, the Range-Odometry based MDS method proposed by [20] has been selected to apply our proposed adaptive weighting scheme. The method is summarized in this section. Although the author wasn't able to explain which MDS variant has been applied in his presented method, the dwMDS method [18] is adopted as backbone method in our research.

A critical challenge for MDS-based localization of mobile WSN is the ambiguity issue of arbitrary rotation and translation of the local maps generated at each estimation step. The Rang-Odometry based MDS introduces the odometry measurement into the proximity matrix and augment the node set by including the nodes at both the current and last estimation-step in the mobile scenario. During each estimation, the state of the nodes at the two sequential steps are estimated. So that the augmented node sets between the current and last estimation step have n overlap nodes which can be used to align the local maps generated at each estimation step to realize propagation estimation for mobile WSN.

In this paper, the Range-Odometry based MDS method is applied to estimate velocity state of the UAV set based on the FDOA measurement and accelerometer measurement as shown in the green block in Fig 1. The augmented node set at the MDS estimation-step k is denoted as $\overline{\mathbf{\Lambda}}^{(k)} = \left\{\mathbf{\Lambda}^{(k-1)}, \quad \mathbf{\Lambda}^{(k)}\right\}$. The corresponding proximity matrix of the node set is constructed as below:

$$\mathbf{U}^{(k)} = \begin{bmatrix} \mathbf{M}^{(k-1)} & \mathbf{\Delta}^{(k)} \\ \mathbf{\Delta}^{(k)} & \mathbf{M}^{(k)} \end{bmatrix}, \tag{1}$$

The velocity state of the node set $\overline{\mathbf{\Lambda}}^{(k)}$ is estimated by minimizing the following global cost function which is also known as STRESS function:

$$S(\overline{\mathbf{V}}^{(k)}) = \sum_{1\leq i\leq 2n} \sum_{\substack{1\leq j\leq 2n \\ j\neq i}} \omega_{ij}^{(k)} (u_{ij}^{(k)} - v_{ij}^{(k)}(\overline{\mathbf{V}}^{(k)}))^2, \tag{2}$$

where $u_{ij}^{(k)}$ is the measurement and $u_{ij}^{(k)} = \mu_{ij}^{(k)}$ when $i \neq j$, and $u_{ij}^{(k)} = \delta_{ij}^{(k)}$ when $i = j$. $v_{ij}^{(k)}$ is the velocity proximity estimation between the two nodes at the augmented node set which is a function of $\overline{\mathbf{V}}^{(k)}$. $\overline{\mathbf{V}}^{(k)}$ is the velocity estimation of the node set $\overline{\mathbf{\Lambda}}^{(k)}$. $\omega_{ij}^{(k)}$ is a weight factor for measurement $u_{ij}^{(k)}$ which is adaptive based on the estimation residual at the last estimation-step $k-1$. The detailed definition can be found in the following section.

C. Adaptive Weighting Scheme

As aforementioned, the weight factor $\omega_{ij}^{(k)}$ in the cost function (2) represents the accuracy of the measurement $u_{ij}^{(k)}$. Arrange all the weight factor $\omega_{ij}^{(k)}$ in the weight matrix $\mathbf{\Omega}^{(k)}$, where:

$$\mathbf{\Omega}^{(k)} = \begin{bmatrix} \mathbf{\Omega}_M^{(k-1)} & \mathbf{\Omega}_\Delta^{(k)} \\ \mathbf{\Omega}_\Delta^{(k)} & \mathbf{\Omega}_M^{(k)} \end{bmatrix}, \tag{3}$$

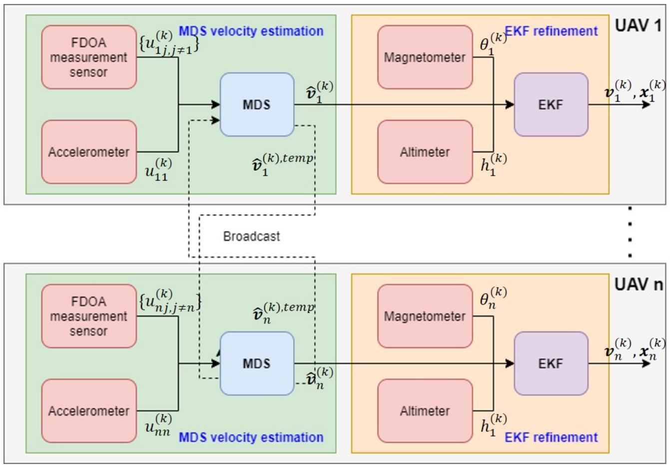

Fig. 1. **system architecture of adaptive MDS-EKF refinement framework.**

where the $\mathbf{\Omega}_M^{(k-1)}$, $\mathbf{\Omega}_\Delta^{(k)}$ and $\mathbf{\Omega}_M^{(k)}$ are the weight metrics for $\mathbf{M}^{(k-1)}$, $\mathbf{\Delta}^{(k)}$ and $\mathbf{M}^{(k)}$ respectively. In the noise unknown environment, the weight factor of each measurement is initialized as unit value and updated at the end of each MDS estimation-step. Inspired by the noise variance update function applied in the Sage-Husa Adaptive Kalman Filter [21], the update equation is defined as:

$$\omega_{ij}^{(k+1)} = (1 - d_k) \cdot \omega_{ij}^{(k)} + d_k \cdot (e_{ij}^{(k)})^s, \tag{4}$$

where d_k is a coefficient defined as:

$$d_k = \frac{1-b}{1-b^{k+1}}, \tag{5}$$

where b is the forgetting factor which is set as 0.9 in this paper. s is the amplification factor which is set as 6 in this paper. e_{ij} is the normalized residual between the measurement of relative velocity or velocity change and its corresponding estimation value and is defined as:

$$e_{ij} = \left| \frac{v_{ij} - u_{ij}}{u_{ij}} \right| \tag{6}$$

However, we admit that the (6) has a singularity issue when the two UAVs are static to each which causes the u_{ij} to become nearly zero.

D. Local Map Registration

In order to resolve the ambiguity issue of the local map up to an arbitrary rotation and translation generated at each estimation step, at least three stationary UAVs are required in the UAV set $\mathbf{\Lambda}$ to achieve precise coordinate system registration according to the reference [20]. In this paper, we are not limited by this precondition through avoiding state estimation of the nodes $\mathbf{\Lambda}^{(k-1)}$ at the MDS estimation-step k. There are n overlap nodes $\mathbf{\Lambda}^{(k-1)}$ between the two sequential node set $\overline{\mathbf{\Lambda}}^{(k-1)}$ and $\overline{\mathbf{\Lambda}}^{(k)}$ which have the same coordinate value in their respective local maps. When $n > 3$, the transformation matrix between the two maps is identity matrix. Therefore, we consider the local map generated at each estimation-step is automatically aligned with the fixed coordinate system.

E. Extended Kalman Filter

At the second stage, an EKF-based estimator is applied to refine the initial velocity estimation of UAV i and generate the position estimation which is the yellow block as shown in Fig 1. Set $\mathbf{X}_i^{(k)} = \begin{bmatrix} x_i^{(k)} & y_i^{(k)} & z_i^{(k)} & v_{x,i}^{(k)} & v_{y,i}^{(k)} & v_{z,i}^{(k)} \end{bmatrix}^T$ as the estimation state of UAV i at the estimation-step k. The input to EKF is denoted as: $\hat{\mathbf{v}}_i^{(k)} = \begin{bmatrix} \hat{v}_{x,i}^{(k)} & \hat{v}_{y,i}^{(k)} & \hat{v}_{z,i}^{(k)} \end{bmatrix}^T$ which is the initial velocity estimation generated by MDS at stage one.

At the EKF update step, the propagation model of state estimation is:

$$\hat{\mathbf{X}}_i^{(k)} = \mathbf{F}\mathbf{X}_i^{(k-1)} + \mathbf{G}\mathbf{u}_i^{(k)} \tag{7}$$

The error covariance prediction is:

$$\mathbf{P}_k^- = \mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^T + \mathbf{Q}, \tag{8}$$

where $\mathbf{Q}$ is the propagation error covariance.

At the EKF measurement update step, the measurements from magnetometer and altimeter of UAV i are introduced. Due to the fact of different update frequency of the measurements, we define the measurement vector depending on the data availability as:

$$\mathbf{z}_i^{(k)} = \begin{cases} \begin{bmatrix} \theta_i^{(k)} & h_i^{(k)} \end{bmatrix}^T, & if \quad both \quad available \\ \theta_i^{(k)}, & if \quad only \quad heading \quad angle \end{cases} \tag{9}$$

where $\theta_i^{(k)}$ and $h_i^{(k)}$ are measured heading angle and altitude of UAV i. The measurement function is:

$$\mathbf{z}_i^{(k)} = h(\mathbf{X}_i^{(k)}) + w_k, w_k \sim N(0, \mathbf{R}), \tag{10}$$

where:

$$h(\mathbf{X}_i^{(k)}) = \begin{cases} \begin{bmatrix} arctan(\frac{v_{x,i}^{(k)}}{v_{y,i}^{(k)}}) & z_i^{(k)} \end{bmatrix}, & if \quad z_i^{(k)} = \begin{bmatrix} \theta_i^{(k)} \\ h_i^{(k)} \end{bmatrix} \\ arctan(\frac{v_{x,i}^{(k)}}{v_{y,i}^{(k)}}), & if \quad z_i^{(k)} = \theta_i^{(k)} \end{cases} \tag{11}$$

$w_k \sim N(0, \mathbf{R})$ is the measurement noise. Kalman gain is generated by the equation:

$$\mathbf{K}_k = \mathbf{P}_k^- \mathbf{H}_k^T (\mathbf{H}_k \mathbf{P}_k^- \mathbf{H}_k^T + \mathbf{R}_k)^{(-1)}, \tag{12}$$

where:

$$\mathbf{H}_k = \left. \frac{\partial h}{\partial \mathbf{X}} \right|_{\hat{\mathbf{X}}_i^{(k)}} \tag{13}$$

State estimation is updated via:

$$\mathbf{X}_i^{(k)} = \hat{\mathbf{X}}_i^{(k)} + \mathbf{K}_k (\mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{X}}_i^{(k)}) \tag{14}$$

The error covariance is updated via:

$$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_k^- \tag{15}$$

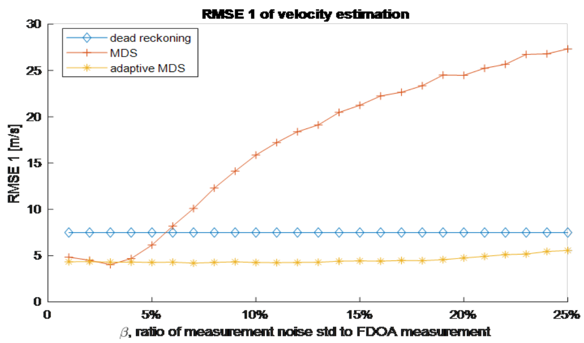

Fig. 2. **velocity estimation RMSE of reference MDS and adaptive MDS applying on a 4-UAV team.**

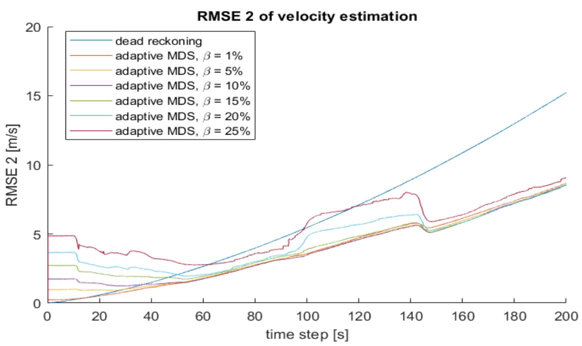

Fig. 3. **velocity estimation RMSE of adaptive MDS applying on a 4-UAV team.**

III. Simulation and Results

To verify and validate the proposed methodology, numerical experiments are implemented in the MATLAB 2021a with 50 Monte Carlo simulations. The UAV in the simulation is assumed as multi-copter aerial vehicle and the speed range of each UAV is $[0, 35]m/s$. The FDOA-based sensor measurement has the update frequency of $10Hz$, and its measurement noise is Gaussian distribution $\omega_{FDOA} \sim N(0, \sigma^2_{FDOA})$. The σ_{FDOA} is proportional to the ground truth of relative velocity and the unit is m/s. The ratio between σ_{FDOA} with the ground truth of relative velocity is denoted as β, representing the measurement noise level of the FDOA-based sensor.

In the first experiment, both the reference Range-Odometry MDS method and the proposed adaptive MDS method are applied to a 4-UAV team. The weight matrix of the reference method is well-tuned when $\beta = 1\%$ and the weight matrix of the adaptive MDS method is pre-set as unit matrix. The result as shown in the Fig. 2, demonstrates significant improvement of robustness of the proposed method comparing with the original reference. However, when examine the estimation RMSE along the flight trajectory of the UAV team as shown in the Fig 3, it is noted that the increase of the FDOA measurement noise causes significant estimation error for adaptive MDS in the initial time-steps. This is because the increase of the FDOA measurement noise leads to the greater accuracy difference between the sub-matrix $\boldsymbol{M}^{(k)}$ and the

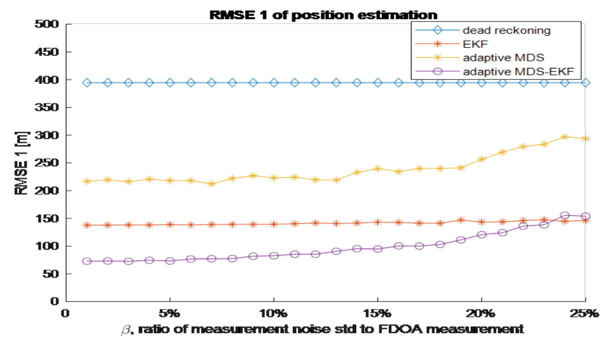

Fig. 4. **position estimation RMSE of adaptive MDS, EKF and adaptive MDS-EKF applying on a 4-UAV team.**

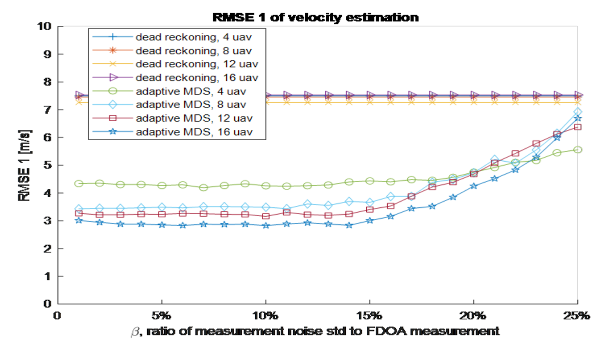

Fig. 5. **velocity estimation RMSE of adaptive MDS with UAV team of different size under different measurement noise.**

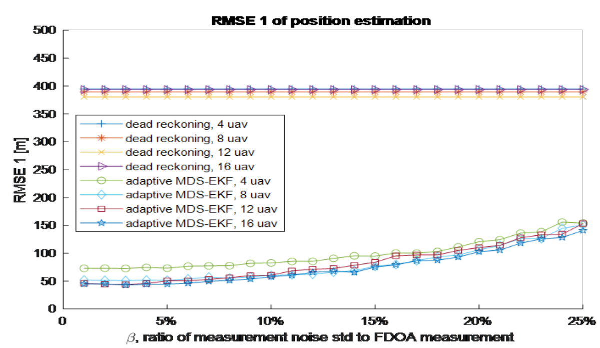

Fig. 6. **position estimation RMSE of adaptive MDS-EKF with UAV team of different size under different measurement noise.**

$\boldsymbol{\Delta}^{(k)}$ and the initialized weight matrix is less accurate to reflect the increased difference. Therefore, the proposed method is sensitive with the weight matrix initialization at the initial estimation steps.

In the second experiment, our proposed adaptive MDS method and the adaptive MDS-EKF refinement framework are applied to a 4-UAV swarm along with the benchmark EKF method as shown in Fig 4. The proposed refinement framework effectively improves the estimation precision on the basis of the adaptive MDS method and outperforms the benchmark EKF method when $\beta < 23\%$, although its estimation error increases faster than EKF when the measurement noise becomes greater.

In the third experiment, as shown in Fig. 5 and Fig. 6, the estimation RMSE of adaptive MDS method and the refinement framework are decreased with 21.6% and 23.4% respectively while applying to the UAV team with team size increasing from 4 to 16. This is because the increased UAV team size generates more measurement data to the MDS which is beneficial to increase its estimation accuracy [9, Chapter 3].

IV. Conclusion & Future Work

Swarm UAV and drone control is important for collaborative applications such as future smart cities and provide flexible capacity in adaptive SONs [2], [3]. In this paper, the proposed adaptive weighting scheme has been proved to increase the robustness of both the weighted MDS method and the MDS-EKF refinement framework when applying in the noise unknown environment based on the numerical experiment results. Although the localization method in this article is based on FDOA velocity measurement for mobile WSN, we believe that the weighting scheme can also be applied to MDS method for stationary WSN localization based on distance or other non-distance RF measurements. As the next-step work, this will be further studied and validated, especially for physics informed trajectory estimation [22], and overlapping data channels [23]. Furthermore, the method in this article only relies on velocity measurement although FDOA can typically derive both velocity and distance information. In the future, we will study to further improve the refinement framework by using the unused distance measurements. Besides, we admit that each MDS estimation step are assumed to be well synchronized within each time-step in the simulation which is not always true in reality. The computational complexity and communication complexity because of the iterative SMACOF algorithm in the MDS method is not considered. Its impact on the localization performance in the real application should be further investigated and tested in the field experiment.

References

[1] H. Oh, S. Kim, H.-s. Shin, and A. Tsourdos, "Coordinated standoff tracking of moving target groups using multiple uavs," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 51, no. 2, pp. 1501–1514, 2015.

[2] B.-W. Chen and S. Rho, "Autonomous tactical deployment of the uav array using self-organizing swarm intelligence," *IEEE Consumer Electronics Magazine*, vol. 9, no. 2, pp. 52–56, 2020.

[3] D. Liu, Y. Xu, J. Wang, Y. Xu, A. Anpalagan, Q. Wu, H. Wang, and L. Shen, "Self-organizing relay selection in uav communication networks: A matching game perspective," *IEEE Wireless Communications*, vol. 26, no. 6, pp. 102–110, 2019.

[4] C. Liu, G. Zhang, W. Guo, and R. He, "Kalman prediction-based neighbor discovery and its effect on routing protocol in vehicular ad hoc networks," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 1, pp. 159–169, 2020.

[5] W. Guo, "Partially explainable big data driven deep reinforcement learning for green 5g uav," in *ICC 2020 - 2020 IEEE International Conference on Communications (ICC)*, 2020, pp. 1–7.

[6] L. Ruan, G. Li, W. Dai, S. Tian, G. Fan, J. Wang, and X. Dai, "Cooperative relative localization for uav swarm in gnss-denied environment: A coalition formation game approach," *IEEE Internet of Things Journal*, vol. 9, no. 13, pp. 11 560–11 577, 2022.

[7] B. Yang and E. Yang, "A survey on radio frequency based precise localisation technology for uav in gps-denied environment," *Journal of Intelligent & Robotic Systems*, vol. 103, no. 38, 2021.

[8] N. Saeed, H. Nam, T. Y. Al-Naffouri, and M.-S. Alouini, "A state-of-the-art survey on multidimensional scaling-based localization techniques," *IEEE Communications Surveys Tutorials*, vol. 21, no. 4, pp. 3565–3583, 2019.

[9] I. Borg and P. J. F. Groenen, Eds., *Modern Multidimensional Scaling*, 2nd ed. Springer, 2005.

[10] Y. Fan, X. Qi, and L. Liu, "Fault-tolerant cooperative localization of 3d mobile networks via two-layer filter multidimensional scaling," *IEEE Sensors Journal*, 2020.

[11] Y. Fan, X. Qi, B. Li, and L. Liu, "Fast clustering-based multidimensional scaling for mobile networks localisation," *IET Communications*, vol. 14, no. 1, pp. 135–143, 2020. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/iet-com.2019.0444

[12] W. Li, B. Jelfs, A. Kealy, X. Wang, and B. Moran, "Cooperative localization using distance measurements for mobile nodes," *Sensors*, vol. 21, no. 4, 2021. [Online]. Available: https://www.mdpi.com/1424-8220/21/4/1507

[13] R. Chen, B. Yang, and W. Zhang, "Distributed and collaborative localization for swarming uavs," *IEEE Internet of Things Journal*, vol. 8, no. 6, pp. 5062–5074, 2021.

[14] M. Wei, R. Aragues, C. Sagues, and G. C. Calafiore, "Noisy range network localization based on distributed multidimensional scaling," *IEEE Sensors Journal*, vol. 15, no. 3, pp. 1872–1883, 2015.

[15] X. Fang, Z. Jiang, L. Nan, and L. Chen, "Noise-aware localization algorithms for wireless sensor networks based on multidimensional scaling and adaptive kalman filtering," *Comput. Commun.*, vol. 101, no. C, p. 57–68, Mar. 2017. [Online]. Available: https://doi.org/10.1016/j.comcom.2016.10.011

[16] S. Zhang, B. Zhang, J. E. Meng, and Z. Guan, "A novel node localization algorithm for anisotropic wireless sensor networks with holes based on mds-map and ekf," in *2016 IEEE Region 10 Conference (TENCON)*, 2016, pp. 3022–3025.

[17] Y. Song, I. Bajaj, R. Rabiee, and W. P. Tay, "Anchor-free multi-level self-localization in ad-hoc networks," in *2021 IEEE Wireless Communications and Networking Conference (WCNC)*, 2021, pp. 1–6.

[18] J. A. Costa, N. Patwari, and A. O. Hero, "Distributed weighted-multidimensional scaling for node localization in sensor networks," *ACM Trans. Sen. Netw.*, vol. 2, no. 1, p. 39–64, 2006. [Online]. Available: https://doi.org/10.1145/1138127.1138129

[19] H.-W. Wei, R. Peng, Q. Wan, Z.-X. Chen, and S.-F. Ye, "Multidimensional scaling analysis for passive moving target localization with tdoa and fdoa measurements," *IEEE Transactions on Signal Processing*, vol. 58, no. 3, pp. 1677–1688, 2010.

[20] B. Beck, R. Baxley, and J. Kim, "Real-time, anchor-free node tracking using ultrawideband range and odometry data," in *2014 IEEE International Conference on Ultra-WideBand (ICUWB)*, 2014, pp. 286–291.

[21] M. Narasimhappa, P. Rangababu, S. L. Sabat, and J. Nayak, "A modified sage-husa adaptive kalman filter for denoising fiber optic gyroscope signal," in *2012 Annual IEEE India Conference (INDICON)*, 2012, pp. 1266–1271.

[22] A. Perrusquia and W. Guo, "A closed-loop output error approach for physics informed trajectory inference using online data," *IEEE Transactions on Cybernetics*, 2022.

[23] C. Fan, B. Li, J. Hou, Y. Wu, W. Guo, and C. Zhao, "Robust fuzzy learning for partially overlapping channels allocation in uav communication networks," *IEEE Transactions on Mobile Computing*, vol. 21, no. 4, pp. 1388–1401, 2022.