Emitter Localization using Geometry Aware UAVs

Christopher L. Peters
Darwin Deason Institute for Cyber Security
Southern Methodist University
Dallas, TX, USA
peterscl@smu.edu

Mitchell A. Thornton
Darwin Deason Institute for Cyber Security
Southern Methodist University
Dallas, TX, USA
mitch@smu.edu

***Abstract*—This study presents a geometry-aware position controller for a small array of cooperative unmanned aerial vehicles (UAVs) to localize an unknown-location emitter in a dense multipath environment. The UAVs operate as dynamically repositioning sensors that are controlled by a deep Q reinforcement learning network optimized by geometry shaping and reduction of elliptical error probable (EEP) through fusion of time difference of arrival and received signal strength measurements. Monte Carlo simulations show orders-of-magnitude reduction in localization error in very few measurement steps and the ability to perform accurate localization with as few as six UAV sensors.**

***Index Terms*—localization, UAVs, TDOA, DQN**

I. Introduction

The technological evolution of autonomous unmanned aerial vehicles (UAV) and cooperative swarms of these systems (UAS) has enabled enhanced radio frequency (RF) sensing applications that exploit the dynamic mobility of the UAVs [1]–[3]. This paper extends [4] with DQN-based online geometry adaptation for emitter localization in dense multipath. The application in this paper is a small UAS swarm (six or more elements) geolocating an emitter that is at an unknown location in a dense multipath environment, such as an urban area. A system that can accurately locate an emitter within a few measurements of its signal has strategic advantages in search and rescue missions, spectrum monitoring, and electromagnetic spectrum operations. We consider for this study an emitter broadcasting a 5 GHz signal from an unknown location in a 1600 m x 1600 m x 500 m urban region. Each UAV is airborne and self-positioned with $\sim$2 cm accuracy (aided by on-board LIDAR); the sensor clocks are synchronized pre-mission and stabilized by $\sim$10 ns precision CSAC [4].

II. Theory

A. Emitter Localization Approach with Cooperative UAVs

As the N-sensor UAS traverses the measurement space, the system detects an emitter signal at a given time or snapshot. The time difference of arrival (TDOA) τ_{ij} across all UAVs $i, j, ...N$ and their positions P_i are processed by the LOCA [5] localization algorithm to determine an emitter location estimate $\widehat{e}$. With six or more UAVs all collecting a single measurement snapshot, a cloud Λ_f of emitter location estimates $\widehat{e}_i$ is generated, which is refined to remove outliers. Because dense-multipath reflections can leave the filtered solution cloud skewed, the per-timestep LOCA estimate is tracked by the median rather than the mean: $\widehat{e}_m = \mathrm{median}(\Lambda_{\mathrm{f}})$.

B. Localization Cloud Error Metrics

In an ideal geometry with minimal UAS positioning errors and time of arrival errors, a localization cloud would be tightly clustered with minimal dispersion of $\widehat{e}_i$ estimates from $\widehat{e}_m$. However, these errors are inherent to the hardware design and especially increased in a dense multipath environment where building reflections impact signal propagation. The underlying geometry of LOCA can improve localization accuracy by repositioning the UAS array into a configuration that minimizes the spread of Λ_{f} [4].

The localization estimate quality can be expressed in terms of the spherical error probable (SEP) radius, denoted SEP_{50} for the median case, representing the region containing the estimated location Λ_{f} with probability 50% [6]:

$$SEP_{50} \;=\; q_{0.5}\{\|\widehat{e}_m - \Lambda_{\mathrm{f}}\|_2\}\,, \tag{1}$$

where $q_{0.5}\{\cdot\}$ denotes the 0.5 quantile (median) operator.

To quantify localization uncertainty, we calculate elliptical error probable (EEP) in azimuth and elevation planes from the filtered solution cloud. Following standard confidence-ellipse theory [7], if the in-plane cloud is locally approximated as Gaussian, the probability-p ellipse is given by the quadratic form $(\mathbf{x}-\boldsymbol{\mu})^{\mathsf{T}}\Sigma^{-1}(\mathbf{x}-\boldsymbol{\mu}) \;\le\; \chi_2^{2\,-1}(p)$. The covariance matrix formed from the estimate cloud Λ_{f} is calculated for the azimuth and elevation planes. Let $\lambda_1 \geq \lambda_2$ be the eigenvalues of the in-plane covariance; then the EEP semiaxes are [8]:

$$a = \sqrt{\chi_2^{2\,-1}(p)\,\lambda_1}, \qquad b = \sqrt{\chi_2^{2\,-1}(p)\,\lambda_2}. \tag{2}$$

Azimuth $(a_{\mathrm{az}}, b_{\mathrm{az}})$ is calculated in the horizontal x–y plane. Elevation $(a_{\mathrm{el}}, b_{\mathrm{el}})$ is computed by the plane spanning the dominant horizontal uncertainty direction and the vertical axis to provide a meaningful 2D slice for elevation error analysis.

The approximate radius, in terms of azimuth EEP_{Az} and elevation EEP_{El}, is derived from the EEP semiaxes with a probability that depends on the ellipse eccentricity [8]:

$$EEP_{\mathrm{r}} \approx 0.75\,\sqrt{a^2+b^2}. \tag{3}$$

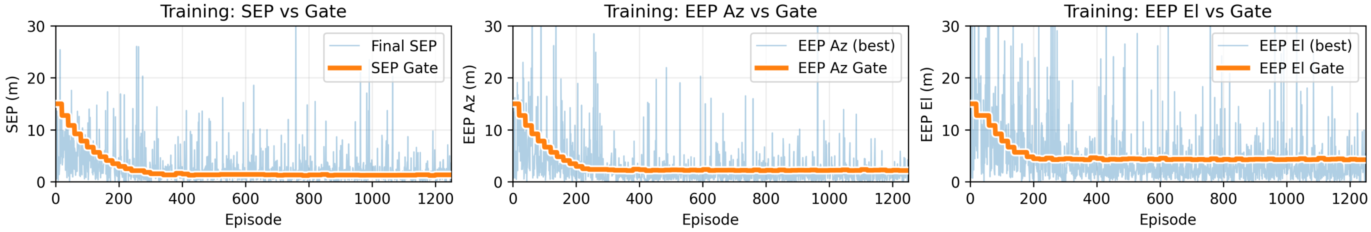

Fig. 1. DQN geometry-aware cloud metrics targets annealing across training steps, with thresholds achieved: SEP_{50} ∼1 m, EEP_{Az} ∼2 m, and EEP_{El} ∼4 m.

C. Deep Q-Network Geometry Controller

The UAV geometries are controlled by a deep Q-network (DQN) with two fully-connected layers, dropout regularization, and an experience replay buffer [9]. DQN was selected for this study because the controller uses a discrete repositioning action set and a reward-driven geometry optimization objective.

The DQN state features observe the above metrics (P_i, τ_{ij}, Λ_{f}, $\widehat{e}_m$, SEP_{50}, EEP_{Az}, EEP_{El}) and the emitter received signal strength for each UAV: $RSS_{i...N}$. Further, we track the Euclidean distance d_i from P_i to $\widehat{e}_m$, considering the performance of [4] where localization accuracy improved significantly as the UAVs found equidistance around the emitter.

The DQN is rewarded by UAS position-based actions that (I.) reduce the cloud error metrics and (II.) stabilize d_i so the UAVs form a pseudo-column around the emitter, aided by RSS_i. Minimizing the per-axis EEP from the cloud allows the system to optimize its geometry in the field-of-view context and reduce the emitter localization error. Additionally, during training (when the emitter position is known), the network is rewarded by decreases in localization error L_e so that it receives additional features to learn optimized geometries.

III. Evaluation Results and Conclusion

The system was evaluated in a Python/Gymnasium Monte Carlo environment [10]. Stochastic propagation models from [11] were implemented to simulate a dense urban multipath environment. The DQN was trained for 1250 random initial UAV and emitter positions with 6-to-9 UAVs. To minimize repositioning steps, training was gated by annealing SEP_{50}, EEP_{Az}, EEP_{El} and L_e targets, so that as the policy learned macro optimal geometries in early stages of training, it would get refined to a goal of 2 m SEP and EEP. The annealing gates are visualized in Fig. 1 showing the achievement of a minimized threshold over training cycles.

The policy was evaluated across 250 episodes for each of 6-9 UAS swarm sizes and target gates SEP_{50}= 1 m, EEP_{Az}= 1.5 m, and EEP_{El}= 2 m. The nominal system localization performance, shown as the median at each repositioning step across all episodes per UAS size in Fig. 2, improves significantly and converges in as few as five steps for 7+ UAS swarm sizes. The larger UAS sizes have denser solution clouds, enabling more refined estimates with fewer measurements.

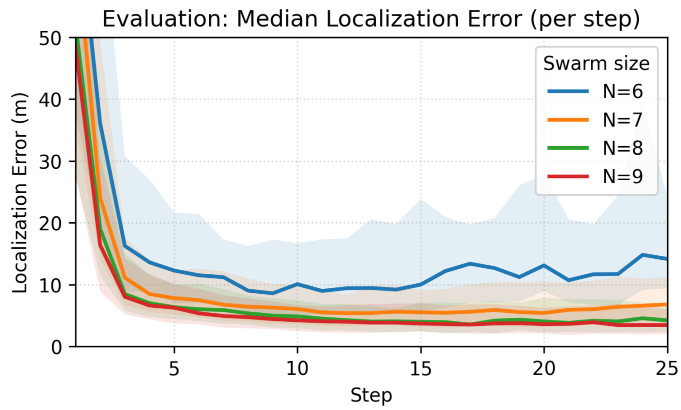

Fig. 2. DQN geometry-aware median localization error performance for swarm sizes of 6 to 9 UAVs with shaded standard deviation.

Overall, these results indicate that geometry-aware DQN control can rapidly converge a cooperative UAS toward optimal localization performance with minimal sensing steps.

References

[1] S. Wu, "Illegal radio station localization with UAV-based Q-learning," China Commun., vol. 15, no. 12, pp. 122–131, Dec. 2018.

[2] A. Guerra, F. Guidi, D. Dardari, and P. M. Djurić, "Reinforcement learning for joint detection and mapping using dynamic UAV networks," IEEE Trans. Aerosp. Electron. Syst., vol. 60, no. 3, pp. 2586–2601, Jun. 2024.

[3] M. Shurrab, R. Mizouni, S. Singh, and H. Otrok, "Reinforcement learning framework for UAV-based target localization applications," Internet of Things, vol. 23, Art. no. 100867, 2023.

[4] C. Peters and M. A. Thornton, "Reducing emitter localization error in urban environments with geometry adaptive UAS arrays," in Proc. IEEE Syst. Conf. (SysCon), Montreal, QC, Canada, 2025, pp. 1–8.

[5] R. O. Schmidt, "A new approach to geometry of range difference location," IEEE Trans. Aerosp. Electron. Syst., vol. AES-8, no. 6, pp. 821–835, Nov. 1972.

[6] W. E. Hoover, "Algorithms for confidence circles and ellipses," U.S. Nat. Ocean Service, Office of Charting and Geodetic Services, NOAA Tech. Rep. NOS 107 C&GS 3, 1984.

[7] D. J. Torrieri, "Statistical theory of passive location systems," IEEE Trans. Aerosp. Electron. Syst., vol. AES-20, no. 2, pp. 183–198, 1984.

[8] NASA, "Calculating the CEP (circular error probable)," NASA-CR-182996, 1987. [Online]. Available: https://ntrs.nasa.gov/citations/19890002104/

[9] V. Mnih *et al.*, "Human-level control through deep reinforcement learning," Nature, vol. 518, no. 7540, pp. 529–533, 2015.

[10] Farama Foundation, "Gymnasium," [Online]. Available: https://gymnasium.farama.org/

[11] International Telecommunication Union, "Propagation data and prediction methods for the planning of short-range outdoor radiocommunication systems and radio local area networks in the frequency range 300 MHz to 100 GHz," Recommendation ITU-R (P.1411–12), Aug. 2023.