# Optimized motion strategy for active target localization of mobile robots with time-varying connectivity

EXTENDED ABSTRACT

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***Abstract*— This paper addresses optimal trajectory generation for active target positioning using a collective localization scheme under a time-varying observation topology. We show that a team of assisting robots using the optimal trajectories can improve the localization accuracy of leader robots whose commands are assigned by high-level tasks. We apply the standard centralized extended Kalman filter to estimate all robot positions by using distance-only relative measurements. In this work, we also explicitly consider the limits on the maximum ranging distance within which the robots are able to make pairwise measurements. The trace of the covariance sub-matrix corresponding to the leader robot's position estimate is selected as the optimization criterion. Simulation results are presented that demonstrate the applicability of this method and provide insights into the difficulties in optimizing this problem.**

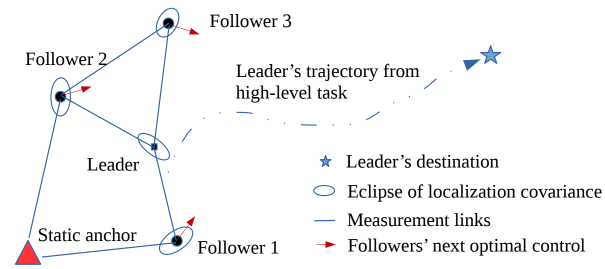


Fig. 1. One leader robot is executing its high-level task while localizing itself. A static anchor with known position and some assisting robots are used to reduce the leader's localization uncertainty via relative ranging-only measurements. Followers also need to estimate their positions by those measurements, thus their movements are controlled to minimize the leader's localization uncertainty.

## I. INTRODUCTION

Active and optimal motion strategy design in cooperative localization (CL) of multi-robot systems (MRS) has drawn more and more attention due to the versatility and range of applications that robotic teams can provide. These include environmental monitoring [1], surveillance [2], object tracking [3], search and rescue [4] as well as active SLAM [5], which have been proposed in the last few decades. As shown in Fig. 1, in this paper, we focus on a new CL task where an active motion strategy is generated under a time-varying topology. Our motivation arises from the need to autonomously navigate while accomplishing a predefined mission within a critical GNSS denied environment.

CL schemes have provided primary method to simultaneously estimate all robot positions and their covariance matrix with only relative observations and local odometry in a centralized [6]–[8] or distributed [9]–[11] manner. However, concerning the active strategy of the robot team, only a few operations have been developed, such as the frequency optimization of communication [12] or optimal formation design [13], [14]. There are several problems that are similar to our mission, like the CL and active target tracking (CLATT) problem [15]–[20], active information acquisition by cooperative robots [21]–[23] and active SLAM with multiple robots [24]. However existing works either rely on perfect knowledge of the robots' positions, or requires many landmarks to ensure enough data association. Here we consider the case where all robots need to estimate their positions while planning and mutual observation is the only source of data under an explicit time-varying topology.

The main contributions of this paper are a new multi-robot CL scheme wherein several followers are used to help improve the leaders' self-localization with time-varying measurement topology as well as an optimization framework for this problem. In this paper, firstly, a binomial regulation function (RF) is introduced into the measurement model to further explicitly explain the loss or resurgence of an observation. Then a centralized standard EKF from the CL framework is implemented for estimation. Lastly an optimizer is designed based on the current estimates and the optimality criterion is chosen as the trace of the covariance matrix corresponding to all leaders.

We evaluate our method over 100 Monte-Carlo simulations with up to 20 robots (1 leader and 19 followers) and 1 anchor. Our results show that by using our proposed optimization strategy, the leader's localization uncertainty is lower than the cases where all followers either remain static or mimic the control of the leader.

## II. TASK ILLUSTRATION

As shown in Fig 1, consider a group of **M leaders**, and **N followers** moving on plane and **O static anchors**. There are both proprioceptive and exteroceptive sensors equipped on the robots (i.e. leaders and followers). The exteroceptive ranging measurement is limited by the relative

This work was funded by the National Natural Science Foundation of China (61374213 and 61573247), and the authors gratefully acknowledge financial support from China Scholarship Council.

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distance, which means only robots within a known threshold (the maximum ranging distance) are able to measure and communicate their relative distance. This results in a time-varying connection topology. The objective of this system is to design optimal motion strategies for the followers so that the localization accuracy of the leaders can be improved across the executing time of the high-level tasks.

## III. PROBLEM FORMULATION

The range-only measurement model with RF is,

$$z_{ij}(k) = s_\rho(r_{ij}(k))r_{ij}(k) + v_{ij}(k), \tag{1}$$

where $r_{ij}(k)$ is the real distance and $s_\rho$ is the RF, where $s_\rho(r_{ij}(k)) = \begin{cases} 1, & r_{ij}(k) \le \rho \\ 0, & r_{ij}(k) > \rho \end{cases}$. The Ricatti recursion from the centralized and standard EKF gives,

$$\boldsymbol{P}_{k|k} = \left(\boldsymbol{P}_{k|k-1}^{-1} + \boldsymbol{H}_k^T \boldsymbol{R}_k^{-1} \boldsymbol{H}_k\right)^{-1}. \tag{2}$$

Resulting in the optimization problem,

$$\begin{array}{ll} \underset{\boldsymbol{u_1},\ldots,\boldsymbol{u_N}}{min} & trace(\boldsymbol{P}_{L_k}) \\ s.t. & abs(\boldsymbol{u_i}) \le \tau \boldsymbol{I}_{2\times 1}, i \in \{1, 2, ..., N\}_F. \end{array} \tag{3}$$

where $\boldsymbol{P}_{k|k} = [\boldsymbol{P}_{F_k} \quad * \quad ; \quad * \quad \boldsymbol{P}_{L_k}]$ and subscripts $F$ and $L$ refer to the matrix components related to followers and leaders, respectively.

## IV. SIMULATION AND DISCUSSION

Our tested MRS configurations are presented in Table I, including the number of different robots, anchors as well as the network topology, where “TV” stands for time-varying network and “FC” is fully connected topology all the time. In all simulation cases, follower robots that were controlled according to (3) result in the lowest localization uncertainty of the leader robot, see Figure 2

TABLE I

SIMULATION SCENARIO CONFIGURATIONS

| | O | M | N | G | | O | M | N | G |
|---|---|---|---|---|---|---|---|---|---|
| A | 1 | 1 | 2 | FC | C | 1 | 1 | 2 | TV |
| B | 1 | 1 | 19 | FC | D | 1 | 1 | 19 | TV |

For the smaller team size in configuration A, the mean uncertainties at the final step of the {optimal, mimic, static} data sets are {0.1212, 0.1963, 0.3395}. Our optimized controllers were able to reduce the final mean uncertainty by {38.3%, 64.3%} when compared to the {mimic, static} followers for the fully connected case. In configuration C, the mean values are {0.3606, 0.3425, 0.6590}. The improvement rises to 45.3% when compared to the static followers, but is slightly worse (5.3%) than the mimic followers. The uncertainty distribution also becomes more skewed across time steps. Given the smaller team size, moving out of range of a single follower robot can severely impact the localization performance of the leader. Thus, the longer tails can be partly attributed to cases where a follower robot moved out of range of the leader robot due to noise in its actuation.

In the 20 robot team case, the leader's localization uncertainty is substantially lower due to the increased number of available ranging measurements. Here, the optimal followers obtained more accurate results than the other two types of movement and achieved a further {25.1%, 66.6%} improvement over the final mean uncertainty of the {mimic, static} robots in the scenario B, and {54.7%, 27.6%} in case D. The mean values of the final uncertainties are {0.0109, 0.0146, 0.0327} and {0.0568, 0.1254, 0.0784}, respectively. Notably, the mimic followers produced a much wider distribution of results than either the static or optimal followers when the robots were range-limited. Closer inspection of the team formation showed that the initial formation of the robots makes it harder for the leader robot to create new observation connections compared to losing one due to the presence of motion noise. The same control inputs for all robots are meant to keep the initial topology, but since follower robots are initially distributed across the space, the leader robot is often too far to build new connections, whereas its initial links are easily broken. So applying the same control input doesn't even perform as well as the static followers. The same degeneration didn't occur to the case with fewer followers because the initial topology (triangle) is much more robust. However, it's clear that our proposed control strategy can overcome this challenging condition and thus can yield more improvement when there are more followers.

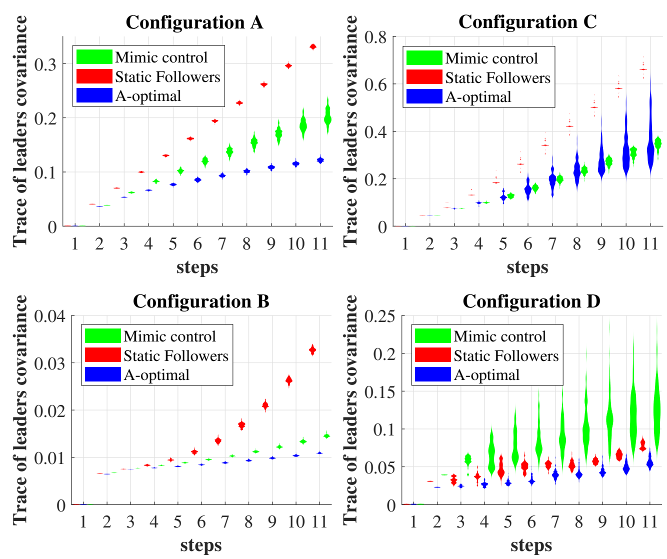


Fig. 2. Distribution of the trace of leader's covariance matrix. Note that the $y$ axis scales are not the same.

## V. CONCLUSIONS

In this paper, we proposed an active localization method in the form of a multi-robot system under a time-varying observation topology. The distance-only measurement model is reformulated and an A-optimality indicator is chosen to design a motion optimizer for the assisting robots. We showed that the main difficulty lay in the inconsistent prediction of the measurement Jacobian matrix. This occurs in the optimizer due to the approximation and from the fact that the estimated positions from the EKF are necessarily stochastic. Future work would include developing a better indicator, as well as a distributed form of our motion strategy generation.

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