# Distributed Accurate Formation Control Under Uncertainty

Robotics Track

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## ABSTRACT

Formation control is a canonical task in the multi-robot teamwork field, where a group of robots is required to maintain a specific geometric pattern, while moving from a start point to a destination. When one assumes imperfection of the sensors of the robots, the goal becomes minimizing the group's deviation from the required pattern (maximizing the formation accuracy). Previous work has considered optimality in an uncertain environment only in centralized setting (or using some form of communication). This work examines the problem of optimal formation accuracy in a distributed setting, while accounting for sensory uncertainty and no communication.

## KEYWORDS

AAMAS; ACM proceedings; Robotics; Teamwork; Formation; Distribute

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## 1 BACKGROUND

Multi-robot formation control is typically defined by the need for a team of robots to travel from start point to goal point, while maintaining a specific predefined geometrical pattern (a.k.a. a formation). The motivation for maintaining the geometrical pattern is to maximize some team utility function, e.g. increasing fuel economy by reducing the air drag in aircraft formations, maximizing the range of the sensing field for probes or sensor networks, and many more.

A quite simplistic, yet very powerful approach that deals with this task is called leader-follower [2, 3]. In its essence, one robot (the *global leader* or *GL*) is taking care of the navigation to goal and every other robot is following some team member, which may or may not be the GL. When a robot follows a team member, said team member is called the *local leader* and the following robot a *follower*. Thus, under the leader-follower approach, chains of followers are created from each robot to the global leader and the positional estimation errors are propagated throughout the chain members, and while may cancel each other out, typically tend to accumulate.

The hierarchical nature of the leader-follower approach reduces the formation maintenance down to two tasks: optimal leader selection for each robot (except the GL), and following a single robot. This paper focuses on the latter, while assuming that no reliable communication can be assured, only some robots can sense the GL, and finally that all sensors are noisy and the robots' estimations of their visible team-members state (pose) are not accurate.

There are many works that assume some subset of the above three assumptions, e.g. a centralized approach in [5] given perfect communication, decentralized in [1] that assume partial communication, or [6] that assume perfect sensing of all team-members. However, to our knowledge, this work is the first to assume all three assumptions together.

Similar to the centralized approach in [4], we present the *Uncertain Leader Selection* (`ULS`) algorithm for *distributed* leader selection that aims to reduce the accumulative error of robots' sensors and increase the formation stability without relying on communication. Additionally, considering extremely noisy, or even hostile environments, we present the *Uncertain Virtual Leader Selection* (`UVLS`) algorithm, where instead of following one of the visible members of the team, each robot follows a virtual leader that it derives from every robot it senses at a given moment. This improves the previous algorithm with regards to robot fault tolerance as well as sensing fault tolerance and uses the redundancy to further reduce individual sensing error. Both algorithms utilize a tree-reconstruction algorithm, where each robot derives the most probable tree representing the hierarchy of local leaders from the observed subset of robots from the formation.

## 2 THE ALGORITHMS

Each robot is assumed to have access to the desired formation, as a relative poses matrix $F_{orig}$. It performs state (pose) estimation on the robots within its sensing range and derives the relative deviation matrix, in which each element $\delta_{ij}$ is the magnitude of the difference vector between the current relative pose of the $i^{th}$ robot (to the $j^{th}$ robot) and their *desired* relative pose, coming from $F_{orig}$. Non-visible robots are ignored. The resulting matrix is reduced to the indices of the visible robots.

In order to estimate the accuracy of the visible robots, we modeled the formation as a tree, where the robots are vertices and an edge between two vertices exists *iff* one of them is the local leader of the other (the sensing is assumed to be directed, as in vision, so this structure is in fact a tree). The deviation matrix, obtained from an observation, as described above is treated as the tree distance matrix between the visible robots in that model. We developed an improved version of the `NeighborJoining` algorithm [7, 8] that reconstructs a tree from the distance matrix of the leaves. In the current case, the visible robots are the leaves in a sub-tree of the formation and only that sub-tree is reconstructed.

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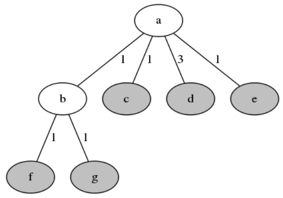
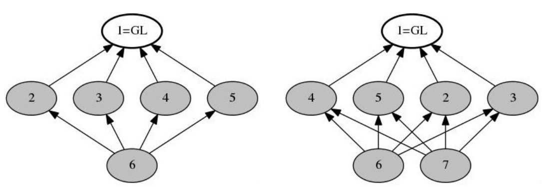



**Figure 1: An example of a tree reconstructed from the set of the leaves ($c$, $d$, $e$, $f$, and $g$). The leaf vertices represent the visible robots from the perspective of some other formation robot, which is not part of the tree. The other vertices represent other robots in the formation, non-detectable by the sensors of that robot. The input tree distance matrix is consistent with the distances between the leaves, e.g. $dist_T(d, f) = 5$ and $dist_T(c, e) = 2$.**

The ULS and the UVLS algorithms use the tree-reconstruction algorithm to reconstruct the current leader-follower relations between the formation robots, starting from the observed set (represented as leaves in the tree), on to their local leaders and to the next local leaders, and so on, until the root, which is assumed to be the GL (or the robot that is the the least common local leader of the part of the formation spawned by the visible set). ULS is used to select the most accurate local leader from the currently visible set, while the UVLS takes into account the entire visible set at given time to construct a virtual local leader. Naturally, the process is repeated for every incoming observation, with some form of smoothing to reduce the possible large effect of outlined observations.

## 3 RESULTS

We present a partial set of results that were obtained from simulations of a formation moving in a straight line, with six or seven robots in a formation, and vision-based state estimations made by the robots. The experiments were performed using the ROS/Gazebo simulator[1,2], simulating the behavior of Hamster robots[3].




(a) 6 robots formation (b) 7 robots formation

**Figure 2: An example of the formation patterns and the robots' ability to sense other team members used in the experiments. Here, robot 1 is the GL and the local leader of robots $2-5$, and robot 6 in 2(a) (and also 7 in 2(b)) can choose any one of robots $2-5$ to follow (or a virtual combination of a subset of them).**

The experiments compared ULS and UVLS to a centralized approach, where there is perfect communication between the GL and the other robots (the GL serving as the central computational unit, in addition to moving the formation). GL checked the noise level (mean) between every pair of robots (as was reported by the noise simulation unit) and assigned the local leaders to all robots in the team. In all experiments, robot #5 did not have an over time increasing noise model and the noise of its sensor was dependent on the distance and angle to the observed robot only. The centralized approach selected it as the best local leader for the robots that could sense it in the formation and the expectation was for ULS to converge to the same selection.

The true distances between each robot and the global leader were recorded at 5Hz rate during the execution and the overall formation error was calculated as the norm of the vector of deviations of each robot from its expected distance to the GL. Similar experiments results were averaged over the time axis to compare between the performance of every method that was put into test.

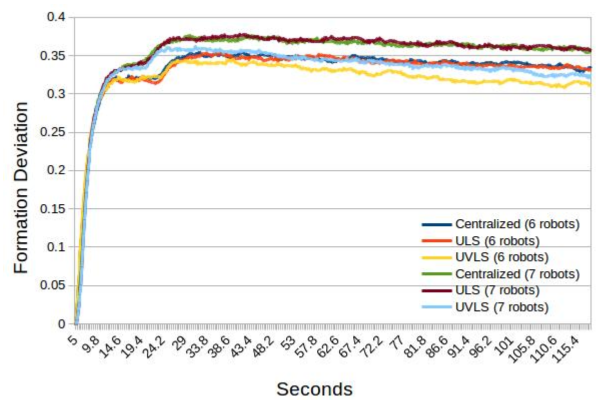



**Figure 3: Average formation deviation over time (lower values correlate to more accurate formation control, i.e., better performance). The actual movement always began at the $5^{th}$ second of the experiment to overcome the asynchronous model loading in Gazebo.**

As can be seen in Figure3, ULS algorithm performed similar to the centralized approach (statistically indistinguishable), while UVLS was statistically significantly better. It is important to note that the virtual local leader accuracy depends on the correlation between the deviations of the state estimations (made by the same robot) and UVLS would not necessarily perform better than the other two algorithms in case of strong correlation between the errors (e.g. if a robot tends to overestimate the distances, or the angles, to the same direction).

## 4 FUTURE WORK

For future work, we plan to extend this work by providing empirical results performed on real robots, while modeling non-holonomic estimation errors, and a more complex navigation scenarios in both simulation and real world.

Additionally, since the main contributor to the runtime complexity of both algorithms is the tree-reconstruction algorithm, there is an ongoing work to replace it with a more efficient reconstruction algorithm, that is not based on NeighborJoining .

[1]http://ros.wiki.com
[2]http://gazebosim.org
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