TEAM: Trilateration for Exploration and Mapping with Robotic Networks

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Abstract—Localization and mapping are often considered simultaneously; however, the use of robotic networks in unknown environment exploration motivates a fundamentally different approach in which robots can act as both mobile agents and instantaneous anchors in a cooperative positioning system. We present Trilateration for Exploration and Mapping (TEAM), a novel algorithm for creating maps of unknown environments with a network of mobile robots. TEAM is designed to leverage the capability of commercially-available ultra-wideband (UWB) radios to provide range estimates with centimeter accuracy and perform anchorless localization in a shared, stationary frame. We provide experimental results in varied Gazebo simulation environments as well as on a testbed of Turtlebot3 Burgers with Pozyx UWB radios. We compare TEAM to the popular Rao-Blackwellized Particle Filter for Simultaneous Localization and Mapping (SLAM). We demonstrate that TEAM (1) reduces the maximum localization error by 50\% (2) requires an order of magnitude less computational complexity (3) reduces the necessary sample rate of LiDAR measurements by an order of magnitude and (4) achieves up to a 28\% increase in map accuracy in feature-deprived environments and comparable map accuracy in other settings.

I. INTRODUCTION

Scientists believe tunnels formed by cooled flowing lava exist below the surface of the moon. These lunar lava tubes may be a favorable environment for human activities because of the protection from radiation, volatile temperatures, and other hazards [1]. Exploring these harsh, remote environments motivates the need for robust autonomous systems. Multi-robot systems have been proposed for this type of mission because of the low volume, mass, and development costs of small robots and the inherent redundancy of multi-robot systems [2], [3], [4].

Robotic networks provide additional advantages over single robot systems because they can cooperate [5], [6], [7], [8]. We explore three types of cooperation: networking, positioning, and task performance. For robots operating in harsh, unknown environments, the loss of communication can render the robot unreachable and therefore useless. If equipped with the capability to forward or re-route data as the network topology or link qualities change, robotic networks can cooperate to overcome this challenge. For robots operating in space, the lack of a Global Positioning System (GPS) or other infrastructure-based localization system presents another challenge. If equipped with the capability to range each other, robotic networks can cooperate to form a local positioning system. For tasks such as mapping, mobile robotic networks can additionally cooperate to cover a terrain in less time or with less uncertainty.

We focus on the application of mapping unknown terrains with light detection and ranging (LiDAR) data and transferring this map data to a base station or lunar lander which we refer to as the data sink. The problem of creating a map of an unknown environment is closely related to the problem of localizing, however we approach them separately and with different sensor modalities. We use UWB radios configured to perform two-way ranging (TWR), i.e. exchanging packets and measuring round-trip time to estimate distance [9]. In this manner, a robot equipped with a UWB radio can determine its position relative to the known positions of three other UWB radios, called anchors. In our robotic network, rather than deploying static anchors in the environment, each mobile robot can act as an instantaneous anchor during positioning, when necessary.

We present Trilateration for Exploration and Mapping (TEAM), a novel algorithm for localization and mapping which requires and leverages the advantages of robotic networks. Via coordinated mobility, peer-to-peer communication, and the ability to trilaterate a position estimate, four or more resource constrained robots can develop accurate maps of unknown environments. The main contribution of this paper is the design and implementation of TEAM which (1) can reduce the maximum localization error by 50\% relative to a Rao-Blackwellized Particle Filter (RBPF) (2) requires an order of magnitude less computational complexity (3) reduces the necessary sample rate of LiDAR measurements by an order of magnitude and (4) achieves up to a 28\% increase in map accuracy in feature-deprived environments and comparable map accuracy in other settings. These benefits are obtained at the cost of a slower overall mapping, as the robots are periodically static in order to trilaterate. We demonstrate TEAM in several simulation environments, as well as on a network of mobile robots.

II. RELATED WORK

Robotic mapping of unknown environments is a well-researched field [10], [11], [12]. The closely related problem of localizing a robot within a map or coordinate frame is also well-researched, with methods including dead-reckoning, active beacons, GPS, landmark-based navigation, and map-matching [13]. In mapping unknown environments, localization and mapping are often referred to as a “chicken-and-
mapping with infrastructure-less UWB positioning. The work is the first to approach multi-robot exploration and the challenge of mapping. To the best of our knowledge, this is presented in [40], however they do not approach the control [38], [39]. Previous work using multi-robot trilateration for the purpose of formation control or leader-follower positioning within a known map [37], or relative positioning with known anchor locations [33], [34], [35], UWB into three categories: infrastructure-based UWB positioning has received some attention. These largely fall support localization for mobile/robotic nodes [30], [31], [32]. Conversely, sensor networks can also anchor nodes can be used to assist localization in wireless sensor networks [29]. Conversely, sensor networks can also aid localization for mobile/robotic nodes [30], [31], [32].

Recently, the use of ultra-wideband technology for robot positioning has received some attention. These largely fall into three categories: infrastructure-based UWB positioning with known anchor locations [33], [34], [35], [36], UWB positioning within a known map [37], or relative positioning for the purpose of formation control or leader-follower control [38], [39]. Previous work using multi-robot trilateration is presented in [40], however they do not approach the challenge of mapping. To the best of our knowledge, this work is the first to approach multi-robot exploration and mapping with infrastructure-less UWB positioning.

III. TRILATERATION FOR EXPLORATION AND MAPPING

The TEAM algorithm can be broken into four modules: initialization, trilateration, mobility, and mapping. TEAM requires four or more robots each equipped with LiDAR for mapping and an ultra-wideband radio for ranging.

A. Initialization

One advantage of TEAM is that it does not require known initial positions, given that each robot has a known and unique identifier. Robot 0’s position defines the map origin and the forward direction. Robot 1’s position defines the y axis and robot 2’s position defines the positive direction of the x axis. Robot 3 and any additional robots can then trilaterate as discussed below. If initial orientations are unknown, an extended initialization sequence can be implemented in which each robot moves a known distance in its local forward direction and re-trilaterates, using the resulting position estimate to determine its orientation. If initial positions are known, TEAM leverages this data to perform Pozyx sensor auto-calibration, estimating the sensor offset from the truth and using that bias to correct future measurements.

B. Trilateration

The process of trilateration involves determining a position estimate from the positions and distances from the three closest anchors, as shown in Figure 1. The grey rings represent uncertainty in the two-way ranging estimate, and the calculated position is the centroid of the curved triangle formed by their intersection points. The curved triangle represents the geometric dilution of precision (GDOP).

In three dimensions, an additional instantaneous anchor is required to trilaterate [41]. Therefore with a robotic network of at least 5 robots, TEAM presents the opportunity to operate in a 3D space and associate data with an accurate position estimate, resulting in 3D maps even if the LiDAR data is two-dimensional.

To prevent UWB signal interference, only one robot should perform trilateration at a time. Therefore, TEAM requires a medium access control protocol [42]. Here we use time-division multiple access (TDMA), meaning each robot is assigned a window of time, t, to perform ranging. The size of this window should be larger than t, the time to measure and average n independent ranging measurements (for our hardware and n = 10, t = 0.47 s). The advantage of TDMA is high utility, i.e. with four robots the UWB channel is in use all of the time. The disadvantage of TDMA is that it requires a predetermined schedule, and for a large, sparse network optimal utility could be obtained by having robots which are out of range with each other trilaterate simultaneously.
For large, intermittently-connected networks, this scheduling problem is non-trivial and should be explored in future work.

We assume additive Gaussian noise for each range estimate, with zero mean and a standard deviation of 10cm [43].

C. Mobility

Robots should synchronize moving and trilaterating for the most accurate measurements; thus the choice of medium access control protocol affects the mobility as well. Using the same TDMA scheme, each robot drives for time $t$ while performing ranging. Then it is stationary for time $3t$ and acts as a localization anchor. To avoid loss of UWB connectivity, this drive window should be much less than the time for a robot to drive beyond the maximum communication range, 90 seconds on our hardware. We select $t = 5s$. We note that this turn-taking results in a system which takes 4 times as long to cover the same distance. For a network of at least 6, this total mapping time can be cut in half assuming only three are stationary at a given time. It may be possible to reduce this time further with other choices of MAC protocol, and this is a direction for future research.

Our autonomous drive module has the following simple control flow: during its drive window, each robot drives forward unless there is an obstacle in its path. If the obstacle is closer to its left, the robot turns right and otherwise it turns left. Optimal drive for exploring an unknown environment with a team of robots has been studied [22], as well as optimal drive for maintaining connectivity [44]. The combination of these objectives, i.e. exploring, maintaining connectivity, and high UWB channel utility is a direction for future research.

D. Mapping

Each time the LiDAR takes a full measurement (360 degrees), the mapping module associates this data with the most recent location estimate calculated by the trilateration module. To ensure synchronization, a delay of more than 100 ms, selected experimentally, between the LiDAR data and the location estimate is considered unacceptable, and this scan data is not processed. When data is associated with a position, it is integrated into the map which is stored as an occupancy grid, a grid where cells take on one of three values: obstacle, free space, or unknown. This map is published periodically (1Hz in our experiments) to be processed by the data sink.

To reduce the burden on the resource constrained robots, the data sink is responsible for merging the maps received from all sources. Using the map merging algorithm from [45], the data sink is able to perform feature mapping and calculate the appropriate frame transforms to merge all received maps. This process does not require synchronization between robots.

IV. Complexity

In TEAM, calculating the location estimate is a constant number of operations in addition to determining the three nearest anchors from the anchors within range, which is also constant time if the network size is constant. Associating scan data with a location estimate depends only on a constant, the size of the scan data. Updating the map can also be done in constant time, as new scans are integrated independent of the size of the existing map.

Following the complexity analysis in [16], the improved Rao-Blackwellized particle filter (SLAM) introduces complexity $O(P)$ each time the location estimate is updated, where $P$ is the number of particles and this computation is associated with computing the proposal distribution, computing the particle weights, and testing if a resample is required. SLAM also introduces complexity $O(P)$ for each map update, and complexity $O(PM)$ each time a resample occurs, where $M$ is the size of the map. For an optimized system, the number of particles required is typically between 8 and 60 [16], depending on the size and features of the environment. Thus TEAM can give up to a 60x reduction in computational complexity. Table IV contains the average runtimes for relevant computations on our hardware.

| Computation          | SLAM, P=60 | SLAM, P=1 | TEAM |
|----------------------|------------|-----------|------|
| Trilaterate          | -          | -         | 0.001 s |
| Update map           | 0.40 s     | 0.1 s     | 0.1 s |
| Process scan         | 2.25 s     | 0.05 s    | < 1 ms |

V. IMPLEMENTATION

A. Data Transfer

The TEAM software is implemented on the popular ROS framework, which provides a publish/subscribe communication paradigm. A single ROS Master at the data sink tracks publishers, subscribers, services, and topics. The role of the Master is to enable individual ROS nodes to establish a peer-to-peer connection at the network layer [46]. Under the assumption that all robots are within the communication range of the data sink, this is sufficient. However, lava tubes are characterized by branches which challenge connectivity [47]. Previous work exploring tunnels has considered a variety of approaches including data tethers and droppable network nodes. This work builds on the approach of [48] with mobile network nodes which can forward or re-route data. The robots and data sink form an ad hoc mesh network, in which robots can act as relays to the data sink when needed, using Optimized Link State Routing (OLSR) to determine network neighbors and appropriate routes [49].

B. Positioning with fewer than three anchors

While three instantaneous anchors are required to get accurate position estimates, TEAM provides a recovery mode when obstacles or distance prevent ranging signals. If only two anchors are available, the robot uses its previous position estimate and odometry as a third point of reference and continues to trilaterate. If less than two anchors are available, the robot relies on solely its odometry to continue updating its location estimate and building its map until anchors become available again.
C. Network Considerations

Delays between the robots and the data sink do not affect the quality of the resulting merged map, as it is processed asynchronously; however, delays or dropped packets between robots could affect the location estimate accuracy. For instance, if a robot’s location estimate is dropped or delayed at the end of its TDMA window, the next robot to trilaterate may start with an incorrect anchor position. To overcome this, TEAM allows a buffer period (expected time 0.3s) between windows which is much greater than the worst delay (400 ns assuming a max distance of 60m) during which the robot continues to publish its position estimate at 10Hz. This ensures the final position estimate during a TDMA window is published on average 3 times, which is suitable to support a conservative packet success rate of 1/3.

VI. Simulation Results

A. Experiments

We use the Gazebo robotics simulator to conduct experiments in various environments referred to as worlds. The Turtlebot3 Burgers come with Universal Robotic Description File (URDF) descriptors compatible with Gazebo, but they do not include Pozyx UWB models. We implemented the Pozyx ranging in Gazebo by modifying the RaySensor Gazebo class, and intend to make this code publicly available. We use the following model:

\[
d_{\text{pozyx}} = \begin{cases} 
    d_{\text{true}} + N(\mu = 0, \sigma = 10\text{cm}), & \text{if } 1_{\text{LOS}} \\
    \text{None}, & \text{otherwise}
\end{cases}
\]

where \(d_{\text{true}}\) is the true distance between two Pozyx devices and \(1_{\text{LOS}}\) is an indicator function which evaluates to true if and only if the RaySensor measurement returns a value greater than or equal to \(d_{\text{true}}\). This indicates line of sight is available, otherwise the simulated Pozyx does not return a ranging estimate.

The first world we consider challenges SLAM but is well-suited for TEAM: a long, featureless, obstacle-free corridor. This environment is difficult for a particle filter because the particle distribution becomes spread as the robots navigate along the hallway which lacks discernible features for localization [16]. The results of this experiment are shown in Figure 2; they indicate that TEAM can significantly improve map accuracy in featureless environments.

The second world we consider challenges TEAM but is well-suited for SLAM: a world with obstacles and branches. In this environment robots spend a significant portion operating in TEAM’s recovery mode, i.e. relying on odometry data. The results of this experiment are shown in Figure 3. TEAM performs well in this setting because the simulated odometry data is quite accurate (variance in \(x\) and \(y\) are each 0.01mm). This factor also contributes to the success of SLAM in this environment, as SLAM relies on the odometry data for all particle updates. We demonstrate the performance of each of these mapping algorithms on noisy odometry data in section VII-B.

Finally, we consider a world with lava tube-like characteristics, including two branches. The Gazebo model for this world comes from [50]. The results of this experiment are shown in Figure 4 and strengthen our claim that TEAM results in accurate maps regardless of the environment.

One significant advantage of TEAM is that it decouples localization from LiDAR sensor measurements. This allows us to reduce the frequency of LiDAR scanning in order to save power; this is useful for robots that have severe energy constraints. Figure 5 shows the result of an experiment in which scans are throttled to 0.1Hz from 5Hz used in the previous experiments. This shows that reduced LiDAR frequency significantly deteriorates the performance of SLAM, while leading to topologically correct albeit sparse maps with TEAM.

As highlighted in section IV the algorithmic complexity...
of SLAM is a function of the number of particles used to capture the belief distribution of the location estimate. For TEAM, the algorithmic complexity is comparable to SLAM with a single particle. In Figure 6 we illustrate the performance of SLAM with 1 particle and TEAM side by side, to illustrate the gain in map accuracy despite the significant reduction in computation.

B. Performance

While the merged map presents a clear picture of the capabilities of TEAM, it is also useful to consider the localization error of the robots over time. For SLAM, the localization varies as the belief distribution changes over time. In feature-deprived worlds like the one shown in Figure 2, this error can grow up to 25m. For TEAM, the localization error is on the same scale as the UWB ranging error or the odometry error in worlds with lots of obstacles/branches. Figure 7 compares the localization error as a function of time during exploration of the lava tube-like world. We observe that errors in TEAM are less than 3m and these errors are infrequent, however errors in SLAM can grow up to 6m and are on average more significant.

It is similarly useful to quantify the accuracy of the merged map created by each algorithm over time. Our map accuracy metric achieves this by measuring the absolute pixel error of map image files which were manually aligned with and compared to the image file of the true world. We plot the map accuracy over time and show that while SLAM and TEAM both result in decreasing map error, TEAM achieves a lower final absolute pixel error (Figure 8). We observe that TEAM achieves a 28% decrease in error relative to SLAM for the world depicted in Figure 2 and a 27% decrease in error for the world depicted in Figure 4.

The results of our simulations strengthen our claim that TEAM can produce more accurate maps in feature-deprived environments and comparable or better maps of other environments. Note that with time-division mobility in the drive module, TEAM generates maps at a considerably slower pace. In simulation, we choose to not model the UWB interference constraint and allow the robots to range simultaneously and therefore drive simultaneously. This allows us to compare SLAM and TEAM across comparable time scales.

VII. TESTBED RESULTS

A. Testbed Overview

Our testbed is comprised of four Turtlebot3 Burgers, each equipped with a RaspberryPi 3B+ running Raspbian, an OpenCR1.0 control board, a 360 Laser Distance Sensor, and differential drive. We have extended each platform with a Pozyx UWB Creator series Anchor, and a USB Wireless Adapter Mideatek RT5370N with 2dBi antenna. The wireless adaptor allows each robot to designate one wireless interface for internet connectivity, and one wireless interface for
joining the TurtleNet ad hoc mesh network. The robots and data sink, a PC running Ubuntu 16.04, all implement Optimized Link State Routing (OLSR), a proactive routing protocol for mobile ad hoc mesh networks [49], [51]. We provide a tutorial for mesh networking Turtlebot3 Burgers [52].

B. Experimental Results

![Fig. 10. SLAM in the hallway: merged map](image1)

Figure 10 shows the merged map created by our testbed in a typical hallway environment using SLAM. Figure 11 shows the map created by a single robot, illustrating the effect of inaccuracy in the odometry readings. We noticed that the drift in odometry was not consistent across the four robots, however the map merging algorithm can correct for this. For better location estimate accuracy, the robots should localize within the merged map rather than their individual maps. Note that for consistency, our time-division drive module was used across all experiments.

Figure 12 shows the merged map created using TEAM. We observe that the wall edges are slightly less well-defined. This is due to noise in the UWB ranging measurements causing small jumps in the position estimate. This noise is primarily attributed to multipath effects, and accounting for these effects in the future will help improve map accuracy. Figure 13 shows the individual map of a single robot and highlights the effect of loss of line of sight. This causes the robot to switch into recovery mode and rely on its odometry until UWB signals are available again, at which point its location estimate may jump, leading to discontinuities in the map. Smoothing this transition will be studied in future work.

VIII. DISCUSSION

A. Scalability

TEAM can be naturally extended to larger networks, by having each robot use its three nearest neighbors as instantaneous anchors. As presented here, the rate at which the robots cover their environment slows as the network grows due to global time-division. Considering each subset of four robots as a group, one research area scalability opens up is group membership maintenance and consensus [53], [54]. For instance, two partitions of four robots each may maintain independent schedules without interference but these group definitions should be flexible to change over time.

B. Synchronization

UWB and LiDAR synchronization is important to map quality. For a time-division ranging/mobility scheme, synchronization across devices is also important. For practical reasons we include a slight buffer between time division windows to prevent conflict. For efficiency, other methods of maintaining tight synchronization should be explored [55], [56].

C. Communication assumptions

In simulation, we assume error-less communication between robots and between robots and the base station unless there is a physical obstacle between two robots. In that case we assume the position estimate data is completely dropped.
This binary connectivity model is unrealistic, and studying how this algorithm performs with lossy line-of-sight channels should be considered further. Experimentally, range estimates are dropped with some probability, even given line of sight. We overcome this by repeating this signal 10 times and taking the average of whatever portion of return signals are received.

For environments with poor communication channels, mobility should be a function of expected delay (i.e. move slow enough that the transmitted position estimate stays accurate). In simulation we assume the robots’ max speed is 0.22m/s and that their relative distances are not more than 60m. This means the robot will not have moved more than 88nm in the time it takes to receive a two-way ranging signal, which is well within the sensor noise, making delays insignificant.

IX. Conclusions and Future Work

We have presented the design, implementation, and evaluation of TEAM, a novel algorithm for localization and mapping in unknown environments with a robotic network. We demonstrate the ability of TEAM to leverage ultrawideband positioning to generate maps of various environments with high accuracy. Our algorithm significantly reduces the computational complexity and the required rate of LiDAR samples, making it suitable for resource-constrained multi-robot systems.

In the future, we propose investigating the use of discrete or continuous belief distributions over the location estimate to capture the randomness in the Pozzy signals. Other improvements could include developing optimal mobility and consensus algorithms to minimize the total time needed to map an area or ideating more sophisticated recovery modes e.g. implementing SLAM when no anchors are available. We additionally plan to characterize multi-path effects on the UWB signals and location estimates and use this environment-driven data to add additional information to the resulting map.

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