Towards Large-Scale Relative Localization in Multi-Robot Systems with Dynamic UWB Role Allocation

Paola Torrico Morón, Jorge Peña Queralta, Tomi Westerlund

Abstract—Ultra-wideband (UWB) ranging has emerged as a key radio technology for robot positioning and relative localization in multi-robot systems. Multiple works are now advancing towards more scalable systems, but challenges still remain. This paper proposes a novel approach to relative localization in multi-robot systems where the roles of the UWB nodes are dynamically assigned between active nodes (using time-of-flight for ranging estimation to other active nodes) and passive nodes (using time-difference-of-arrival for estimating range differences with respect to pairs of active nodes). We adaptively update UWB roles based on the location of the robots with respect to the convex envelope defined by active nodes, and introducing constraints in the form of localization frequency and accuracy requirements. We demonstrate the applicability of the proposed approach and show that the localization errors remain comparable to fixed-role systems. Then, we show how the navigation of an autonomous drone is affected by the changes in the localization system, obtaining significantly better trajectory tracking accuracy than when relying in passive localization only. Our results pave the way for UWB-based localization in large-scale multi-robot deployments, for either relative positioning or for applications in GNSS-denied environments.

Index Terms—UWB; ToF; TDoA; Localization; UWB Ranging

I. INTRODUCTION

Autonomous mobile robots have been penetrating multiple industries and domains of our society. At the same time, their connectivity has been increasing and networked collaborative systems have gained importance within the field [1]. From construction [2] to warehouses [3] to mining, the ability for robots to operate without a user input has become more important [4]. In order to achieve a high level of autonomy and situational awareness, localization is one of the first problems to be solved [5]. Outdoors, GNSS sensors are widely used [6], but multipath propagation and other inherent limitations make this solution unreliable indoors [7], [8]. Localization in GNSS-denied environments often relies on onboard sensors such as IMUs [7], or odometry estimations from lidars [9], [10] or cameras [7], [11]. Onboard methods often have their own limitations in terms of long-term drift, or are affected by the environmental conditions, e.g., low visibility for cameras or lack of structure for lidars [12].

In controlled deployments such as industrial environments, infrastructure can aid in localizing robots. Among the different approaches, radio technologies have gained momentum in recent years [13]. Wi-Fi, Bluetooth ultra-wideband (UWB) technology all can aid in positioning by ranging between signal emitters and receivers, and often also including calculations regarding the angle of arrival of the signal [14], [15]. UWB systems provide more accuracy than both Wi-Fi and Bluetooth [16], and a greater range than Bluetooth [8]. UWB technology features more immunity to multipath fading, better interference mitigation and improved timing [16]. It also provides accurate enough localization indoor for mobile robots, including aerial vehicles, at a significantly lower cost than, e.g., motion capture (MOCAP) systems [17]. Ranging in UWB systems is often based on either time-of-flight (ToF), with an active measurement between a given pair of nodes, or time difference of arrival (TDoA), with the possibility of the node being a passive listener [18].

Albeit the many mobile robotic systems in the literature relying on UWB for localization [16], [19], there are still a number of limitations in terms of deployment flexibility and scalability of these systems. First, a set of stationary nodes, or anchors, at known positions is often used as the basis for the localization of mobile nodes, or tags [18]. Only recently, there have been studies on the mobility of anchors [20], and on the design of multi-robot systems that are entirely mobile [11], [21]. However, these still rely on ToF measurements limiting the scalability of the system, as node-to-node transmissions need to be scheduled within a time window defined by the desired ranging or localization frequency. Scalable TDoA-based systems, e.g., the Crazyflies’ TDoA positioning system [22], have the core limitations of relying in mostly fixed anchors and, independently on whether the anchors are fixed or not, becoming unstable and highly noisy as the mobile nodes move outside the convex envelope defined by the anchor positions.

Motivated by the scalability limitation of UWB ranging in multi-robot systems, we approach the problem by relying on both ToF and TDoA ranging but by dynamically selecting the nodes that are actively using ToF for ranging. This approach allows us to exploit the high scalability of passive TDoA localization, where the main limitation is the physical space available within the ToF nodes. In the rest of this document, we refer to the nodes performing ToF ranging estimations as active nodes or anchor nodes, while the nodes localizing themselves using TDoA are referred to as passive nodes, or listener nodes. The proposed approach relies on UWB nodes that are programmed with custom firmware to act as either active or passive nodes, as well as in a backbone network of ROS 2 nodes in charge of the relative localization estimators,
dynamic role allocation and, in general, data sharing within the robots. We decide on the role of each node by minimizing the global TDoA error based on the position of the nodes. In our experiments, we also utilize VIO estimations that are combined with the UWB positioning information for the navigation of autonomous robots. A conceptual illustration of this process is shown in Fig. 1.

In summary, the core contribution of this paper is the design and implementation of a novel approach to scalable UWB-based localization for multi-robot systems. In relation to the state of the art, this is, to the best of our knowledge, the first one to approach the scalability problem in UWB localization by dynamically switching between ranging modalities. We demonstrate the usability of the method and its improved performance when compared to a standard TDoA approach with fixed anchors. We then show that the dynamic role allocation performs well based on ToF and TDoA ranging, comparing with a baseline that relies on an external MOCAP system. Another modality is the Angle of Attack (AoA) [24], thought it is rarely mentioned and utilized for localization. A technique often employed by Bluetooth is RSSI [8][24].

II. BACKGROUND

There is a clear trend in adopting UWB-based solutions for localizing mobile robots in GNSS-denied environments, with a significant increase in contributions to the existing literature in recent years [18].

Radio-based ranging and localization is not a new approach in mobile robotics. Nonetheless, the high accuracy of UWB compared to traditional Wi-Fi or Bluetooth approaches is enabling the wider adoption, together with lower interference in the bands it operates and enhanced robustness against multipath transmission [8].

For localization purposes, different modalities of ranging exist. These modalities are common to the majority of wireless ranging systems [13]. The two most used ones are ToF, also known as ToA, and TDoA or hyperbolic positioning [23]. Both of these ranging modalities are widely used in research and in the industry, each one with its benefits and draw backs. Another modality is the Angle of Attack (AoA) [24], thought it is rarely mentioned and utilized for localization. A technique often employed by Bluetooth is RSSI [8][24]. Here it is worth mentioning that Bluetooth can be used for positioning for short transmission distances of around a few meters [8], while UWB can be utilized according to [18] up to 60m, and to 150m [25].

A. ToF and TDoA

Ranging estimation based on ToF approaches rely on measurements of the amount of time the signal takes from one node to another, i.e., the time of flight of the signal [7]. ToF measurements are performed one to one between two devices, A and B. This is also called two-way ranging (TWR) which can be single-sided (SS-TWR) or double-sided (DS-TWR) [13]. In short, in SS-TWR a device A initiates the transmission message. When B receives it, it immediately responds, returning the message with the internal delay of the device processing of the signal. Device A can then compute the round trip of the signal and with the delay of B the time of flight. On the other hand, in DS-TWR both devices take turns initiating the communication. It is equivalent to two SS-TWR exchanges [18]. To obtain the position of a mobile node using ToF there needs to be at leas three anchor nodes to range to [26]. Once the distance to each node is computed, the positioning of the node can be computed via multilateration.

The passive TDoA technique measures the difference in the propagation time between a pair of UWB transmitting nodes and one or more receivers [13]. Nodes near active transmitters performing ToF ranging passively intercept the messages and then are able to compute the difference of distance to a pair of nodes and overall its position. It is worth noting that this is not the only approach to TDoA-based localization, as synchronized anchors could act as receivers to a mobile node transmitting signals, without the need for responses. In
this case, however, the location information is available at the anchor system only, unless transmitted to the tag.

1) System scalability: From the two different ranging modalities presented above, ToF lacks scalability owing to time scheduling constraints. The messages in the TWR approach need to be schedule among all the different transmitters and receivers to avoid collisions, and with a limited time bandwidth, each new node added to the system, decreases the communication frequency [27]. Passive TDoA does not present this limitation. Passive nodes intercepting messages for their localization do not actively participate in communication, meaning that more can be added without decreasing the overall frequency of the system [28].

Scalability can be considered a key parameter when a system is deployed in larger areas or for a large number of nodes [13], [29]. When talking about real time systems the rate of update in the nodes is very important, but the number of nodes in the system will limit the frequency of communication [30]. With more UWB nodes in the system, if using ToF, the system will update less frequently having a negative impact in the real time operation [19]. Passive TDoA might provide a solution, since the listener nodes do not participate in the communication and thus do not need any time allocation [28]. However, the drawbacks of this method is the need for clock synchronization [16] and the positioning error dramatically increase when leaving the convex envelope of the anchors [31].

Another alternative solution with regards to scalability is concurrent ranging [13]. A relevant solution in the literature is SnapLoc [16]. The main idea of this solution is a localization system with nodes that can localize with very high update rates. The higher update rates are achieved by using concurrent ranging. Since there exits a previous knowledge of the anchor positions, the tag sends a broadcast message, each anchor then responds with individually delay in the nanoseconds range, avoiding then misclassifcation of the messages due to overlap when all the anchors respond to the tag [16]. The node can then perform TDoA. Due to the need of fixed anchors in known positions, the system is not directly applicable to mobile deployments.

B. UWB in Mobile Robots

Multiple industries utilize or are starting to implement autonomous mobile robots. Warehouse management, mining, or packet deliveries, among others. These applications might not provide a controlled environment for a system based on fixed anchors. Onboard odometry approaches like the use of lidar and VIO, might in time cause drifting and the integration of UWB can aid in correcting it and reducing long-term drift [13], [32].

In the field of UAVs, the centimeter-level accuracy that UWB can provide makes it a cost effective replacement for MOCAP systems and other higher-end solutions, when the accuracy is enough [33]. A typical application for UWB to be used in UAVs is ground to air ranging [34]. Similar techniques can be used also in a swarm of robots [35].

Multiple approaches have implemented sensor fusion with UWB. The use of the Extended Kalman filter [36], Monte Carlo filter [9], moving horizon estimator [37] and even particle filters [2] are some of the examples. There is a clear trend in integrating visual sensors and specifically VIO estimators [13].

III. SCALABLE UWB LOCALIZATION

The majority of the systems implementing localization solutions using UWB are systems that have fixed nodes (anchors) and mobile nodes (tags). These type of solutions do not scale well, normally focusing in the accuracy of the measurements [16]. The two main types of ranging used for UWB are ToF and TDoA, with the majority of them utilizing ToF, with tags being heavily involved in communication. ToF based systems are not very scalable because adding more tags to the system the frequency of the communication decreases, and thus the frequency of the localization for the overall system decreases as well. TDoA systems present a more scalable solution. They normally rely in synchronized anchors that communicate with mobile tags and compute their position. Both types of implementations require the allocation of specific time slots for node communication, making the addition of more nodes into the system, as mention before, reduce the frequency of localization in the entire system. In addition, both types of systems have spacial constraints due to the utilization of fixed anchors.

To create UWB based systems that can easily scale and also have all its nodes be able to mobilize, we propose the following solution. A system that will combine ToF and TDoA ranging approaches, having nodes being able to change the type of ranging they are performing based on its localization...
relative to the system, minimizing the overall error of the system. This solution will thus address the scalability and mobility problems presented before.

The proposed system will have a set number of nodes that are going to act as active nodes for the network. These active nodes will be performing TWR with ToF. The nodes are then going to localize themselves using multilateration and have a relative position with regards to a selected node in the system. These nodes will be able to obtain the distances between each other without synchronized clocks, and more importantly, to provide a solution for a multi-robot system, to be able to have all nodes move and calibrate on the fly. This part of the solution however does not solve the scalability problem.

To address the scalability of the system, the remaining nodes of the system will utilize TDoA to localize themselves. This set of nodes are from now going be referred as listeners due to the fact that implementing passive TDoA localization they will just receive the messages from the active nodes and not transmit any of their own. The TDoA solution implemented will not require to have synchronized nodes, either for the anchors or the listeners, having all the necessary information for the localization solution being passed on the messages from the active nodes. With this implementation, the addition of listeners can technically have no limitation, while in practically depends on computing power present on the distributed system. Listeners can be added to the network and receive the messages from active nodes and have the necessary information to localize themselves with respect to the reference frame being used.

For the solution, the UWB nodes used in the network can be incorporated either in terrestrial or aerial robots. The example in Fig. 1 assumes one node per robot. For the initialization of the network ToF is used, having all-to-all communication between each pair of nodes. Using multilateration, the position of all nodes is computed with the following assumptions:

- The first active node, Active 1, is the initiator of the sequence of communication, and is the point of reference for the localization of the rest of the nodes, it is the origin of the coordinate system.
- The direction from Active node 1 to Active node 2 defines the positive x-axis of the system.
- All the other nodes are in the positive y-axis.

Once the positions are initialized, a subset of nodes is selected based on a desired localization frequency across the whole network, while minimizing the positioning error in individual nodes. The selected subset of nodes functions as mobile anchors in the system. The active nodes keep localizing themselves using ToF, communicating all-to-all continuously. The rest of nodes of the network start localizing themselves using passive TDoA, intercepting the messages of the active nodes and using them to compute the difference of distance between each pair of nodes.

Since all nodes are assumed to be mobile, the subset of UWB nodes that is chosen to be active may not be ideal for all possible configurations, so a role allocation algorithm dynamically changes the role of the UWB nodes as they move, maintaining a the specified number of active nodes for the network. Ideally, the active nodes should be located towards the outside of the system, because the error for the difference of distance for the listener nodes is smaller the closer to the middle of the convex envelope created by the active nodes. Thus, if one of the robots moves more towards the outside, it will change from an active node to a passive listener one.

IV. METHODOLOGY

Through this section, we look into the implementation details and experimental setup.

A. UWB ToF Ranging for anchors

The ranging between two nodes is estimated by implementing either SS-TWR or DS-TWR. The ToF can be computed by (1)

$$ T_{ToF} = \frac{T_{init} - T_{resp}}{2} $$

where $T_{init}$ is the total time since the poll message was sent by the initiator node and the reception time of the response message; and $T_{resp}$ is the time for the replying node to process the poll message and send the reply. This time is sent as information in the response message, where the distance can be obtained. This process is used between the nodes selected as active on the system.

B. UWB TDoA Ranging for anchors

For the TDoA implementation without synchronized clocks a similar computation than before is performed on the listener nodes. Once the initiator nodes has received its response message and computed the respective distance, it sends a new message with the transmission time of the poll message and the reception time of the response message. The TDoA can then be computed by (2)

$$ T_{TDoA} = T_{list} - T_{resp} - T_{ToF} $$

where $T_{init}$ is the time in the listener node between the reception of the poll message and the reception of the response message used for the ToF ranging. With it the difference of distance to each pair of nodes can be obtained.

C. UWB Ranging

Figure 2 shows an exchange of messages between to active nodes performing ToF ranging, and the reception of the messages by one passive listener. Active node 1 initiates the TWR ranging by sending a poll message. Active node 2 response the polling with the necessary information for the distance computation, just as explained above. Then Active node 1 sends a data message with the the necessary information for the listener node to compute the TDoA and the difference of distance, also as explained before. These three messages are all what is needed for all active nodes to position themselves, as well as for the listeners.

The active nodes in the network are in constant communication for the ToF ranging, and for the listeners positioning. They
follow a fixed sequence known by all nodes in the network. A pair of nodes perform TWR, and the pass to the next pair. To ensure that the next pair of nodes continues the communication, a fourth message is added in the communication sequence, the acknowledgement message. This message is sent by the next node in charge of initiating the TWR ranging. This ensures that the network follows the set communication sequence. If the acknowledgement message is not sent before a timeout, the data message is sent again until the response is received.

D. Positioning and role allocation

The previous two approaches can be utilized directly for estimating the position of the nodes. However, as we have discussed, ToF has an inherent scalability problem, while TDoA is only stable for passive nodes moving within the convex envelope defined by the active nodes. Our objective is therefore to limit the number of active nodes to meet the localization frequency requirements, and then dynamically select which subset of nodes are active in order to minimize the positioning error of the passive listeners.

As the passive nodes relies on estimations of differences of the distance to pairs of active nodes, the actual position of the node is then found at the intersection of a series of hyperbolas. To minimize the error, we look into finding the set of nodes to be active such that we minimize the distance from the passive nodes to the centroid of all triangles defined by combinations of three of the active nodes.

We use the following notation for the remaining of this section to describe the position estimators. Let \( |n| = \{1, \ldots, n\} \) be the set of the first \( n \) natural numbers. We assume we have a set of \( n \) nodes with positions \( \{p_i[t] \in \mathbb{R}^3\}_{i \in |n|} \) at a given time \( t \). Let then \( \mathcal{P}(\mathcal{X}) \) represent the set of subsets of \( \mathcal{X} \), and \( \mathcal{P}_k(\mathcal{X}) \) the set of subsets of cardinality \( k \). The objective of the dynamic role allocation algorithm is to find at each time step \( t \) the set of active nodes \( A[t] = \{a_1, \ldots, a_k\}_{a \in |n|} \in \mathcal{P}_k(\mathcal{X}) \), with \( k \) is based on the ranging speed and the minimum localization frequency. The set of passive listeners will then be \( L[t] = |n| \setminus A[t] \). The set of active nodes \( A \) is then calculated by minimizing the following cost function:

\[
A[t+1] = \arg \min_{A \in \mathcal{P}_k(|n|)} \sum_{l \in A} \sum_{i \in |n| \setminus A} \left\| \sum_{t \in T} \frac{P_l[t]}{3} - p_l[t] \right\|^2
\]

where the positions \( p_l[t] \) could have been calculated with either ToF or TDoA depending on whether the node was active at the previous time step, \( l \in A[t-1] \), or not.

Given the set \( A[t] \), we then calculate the positions of all active nodes \( \{p_a\} \) using multilateration and following the assumptions described above, i.e., having the first two anchors defining the direction of the \( x \) axis. The position of a passive listener \( l \in |n| \setminus A \), \( p_l \), is then calculated based on a least squares estimator that minimizes the following cost function:

\[
p_l[t] = \arg \min_{p \in \mathbb{R}^3} \sum_{i \in A, j \in A} \left( d_{ij}^l - (\|p - p_j\| - \|p - p_i\|) \right)^2
\]

Initialy, \( \{p_l[0]\}_{l \in |n|} \) are calculated using multilateration for all nodes as ToF ranging estimations are obtained between all pairs of nodes.

The process above is summarized in Algorithm 1.

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**Algorithm 1: UWB role allocation and relative positioning**

**Input:**
- Maximum number of active nodes: \( k \)
- Node positions at \( t-1 \): \( \{p_i[t-1]\} \in \mathbb{R}^3 \)

**Output:**
- Set of active nodes: \( A[t+1] \in \mathcal{P}_k(|n|) \)
- Set of passive listeners: \( L[t+1] = |n| \setminus A[t+1] \)
- Active node positions: \( \{p_a[t]\}_{a \in A[t+1]} \in \mathbb{R}^3 \)
- Passive listener positions: \( \{p_l[t]\}_{l \in L[t+1]} \in \mathbb{R}^3 \)

**if** \( t = 0 \) **then**

\[
\{d_{ij}\}_{i, j \in |n|, i \neq j} \leftarrow \text{get_tof_ranges}(|n|);
\{p_l[0]\}_{l \in |n|} \leftarrow \text{multilateration}\{d_{ij}\};
\]

**else**

\[
\{d_{ij}\}_{i, j \in A[t], i \neq j} \leftarrow \text{get_tof_ranges}(A[t]);
\{d_{ij}\}_{i \in L[t], j \in A[t], i \neq j} \leftarrow \text{get_tdoa_ranges}(L[t]);
\]

// Active node positions
\( \{p_a[t]\}_{a \in A[t]} \leftarrow \text{multilateration}\{d_{ij}\}; \)

// Passive listener positions
\( \{p_l[t]\}_{l \in L[t+1]} \leftarrow \text{tdoa_ls_estimator}\{d_{ij}\}; \)

// Role allocation
\( A[t+1] = \arg \min_{A \in \mathcal{P}_k(|n|)} \text{tdoa_cost_fn}(\{p_a[t]\}); \)

\( L[t+1] = |n| \setminus A[t+1] \)

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Fig. 3: Set of ROS nodes and other modules in the experiment setup.
DWM1001 module with custom firmware. We have designed and implemented a custom firmware for the DWM1001 modules to be able to act as active or passive nodes. The devices broadcast the ranging information, either ToF or TDoA, from the entire UWB network, so that the position of all nodes can be calculated at any endpoint with all the information available.

F. Robotic platforms

A custom-built UAV was utilized for the experiments. It is based on the X500 quad-rotor frame, embedded with a Pixhawk 5X flight controller running PX4 firmware. We particularly rely on the EKF2 filter in PX4 for controlling the UAV in offboard mode. The onboard computer features an Intel x5-Z8350 QuadCore processor @ 1.44Ghz running Ubuntu 18.04 and ROS Melodic. The UAV is also equipped with an Intel RealSense T265 camera for VIO-based ego-motion estimation. Finally the UAV also has a Decawave DWM1001 UWB node to perform the localization throughout the experimentation.

G. Experiment Setup

All nodes are deployed in an empty room of approximately $40 m^2$ with a MOCAP system that provides the ground truth data. The UAV has one of the UWB nodes mounted and will provide the information of the UWB network to a backbone ROS network where the localization takes place. The node localization algorithms and the role allocation are implemented through a series of ROS nodes, that distribute the information between the different systems, such as forwarding position information to MAVROS for the low-level control of the UAV.

Figure 3 shows the setup used in our experiments from the perspective of sensor drivers, ROS nodes and other algorithms. The UAV relies on fusing the VIO camera data with the flight controller’s internal data to maintain stable flight, while the trajectory and motion planning is calculated entirely based on the UWB localization information. Through the experiments, we use three different position estimation methods (ToF, TDoA and dynamic mode) in addition to the MOCAP system for tracking two different trajectories.

V. EXPERIMENTAL RESULTS

For the experiment setup described above two different flying patterns were tested. The first consisting on a straight line across the room shown in Fig. 4a and the second being a rectangular trajectory shown in Fig. 5a. For each of the patterns four different runs were performed with different positioning methods to compare the proposed solution with baseline ToF and TDoA approaches.

The four runs consist of using the data provided by the MOCAP system to obtain a reference trajectory with the UAV, ToF ranging, TDoA ranging, and the dynamic approach proposed. Each run provides the data for the robot to move in order to follow the predefined trajectory. The UWB nodes set on the experiment room were placed in order to have the node

\[\text{https://github.com/TIERS/dynamic-uwb-firmware}\]
the actual flight path that the UA V has followed and which is reconstructed from the raw UWB positioning data rather than appreciated in Fig. 6a, representing the path that would be followed by the robot.

The unfiltered measurements of the three approaches can be compared to the TDoA approach when the nodes act as a passive listener. The implementation proposed matches the error of the ToF approach for the linear trajectory. As expected the error of the dynamic implementation noticeably improves compared to the others. The error is significantly reduced as individual estimations do not have a significant effect on the robot’s flight. The results show that the dynamic approach is slightly more stable than a standard TDoA method. However, when we look closer in Fig. 7c at the trajectory tracking error from the part of the trajectory where the node switches from TDoA role to ToF and back, the proposed approach outperforms the baseline.

VI. CONCLUSION

We have presented a novel approach to solving the scalability problem in UWB-based relative positioning based on dynamic allocation of active and passive localization roles. With our approach, relative positioning can be estimated within a multi-robot system at a desired frequency, by adaptively selecting the nodes that perform active ToF ranging in order to minimize the expected localization error in passive TDoA nodes. Through a series of experiments using an aerial robot, we demonstrate the applicability of our approach and the improved performance compared to a standard TDoA approach.

In future work, we will look into other optimization methods for the role allocation (e.g., data-driven approaches) while performing larger-scale experiments with multiple mobile ground and aerial robots.

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Fig. 7: Raw UWB positioning error, trajectory tracking error and navigation error in the rectangular trajectory.

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