Distributed Robots Localization and Cooperative Target Tracking

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***Abstract*— This paper focuses on solving the problem of determining relative poses of the N cooperative sensors which include both mobile and stationary, along with position of targets. In the proposed approach, multi robots in a sensor network cooperate with each other in order to localize the position of each target and guide the robot to its assigned target position. The relative poses of neighboring sensors including target will be visually estimated and communicated with to other nearby sensors in the network. In addition, a network communication protocol was developed and implemented based on minimum hardware configuration. The localization and the tracking performance of our proposed approach was evaluated in our experimental hardware set-up.**

Keywords—cooperative localization; indoor positioning; distributed localization.

I. Introduction

There is a potential increase in market for personalised service robotics. Such robots can operate through human assistant or autonomously in order to provide necessary support for the well-being of humans. They can be used for assisting, guiding, educating and entertaining at people homes [1]. One of the most important fundamental functions of service robots is their ability to track people/object in order to either provide continuous service or accomplish instructed task. To follow its target, robust identification process of the robot and its tracking function are needed [2]. In addition to tracking, service robot should be able to localize itself and the target with respect to its given environment while in pursuit.

Target tracking function has been extensively studied and enhanced in many published works. Robots with onboard sensors such as RGB-D (Kinect II) or Laser Range Finders (LRF) are often used for imaging, detection, identification and tracking offering a low cost and reliable sensing modalities [3] [4] [5]. However, if the target is occluded or is beyond the field of view, the service robot may lose tracking of its target which could introduce a challenge in order to initiate a new search for its target. In such scenarios, it would be good idea that more robots are deployed and can collaborate with tracking robot to navigate towards its target. This requires coordinated relative localization among robots for cooperative target tracking.

For example, let us consider a scenario demonstrated in Figure (1) where a group of robots (some mobile and some stationary) equipped with sensors are deployed in order to assist a service robot in tracking a target.

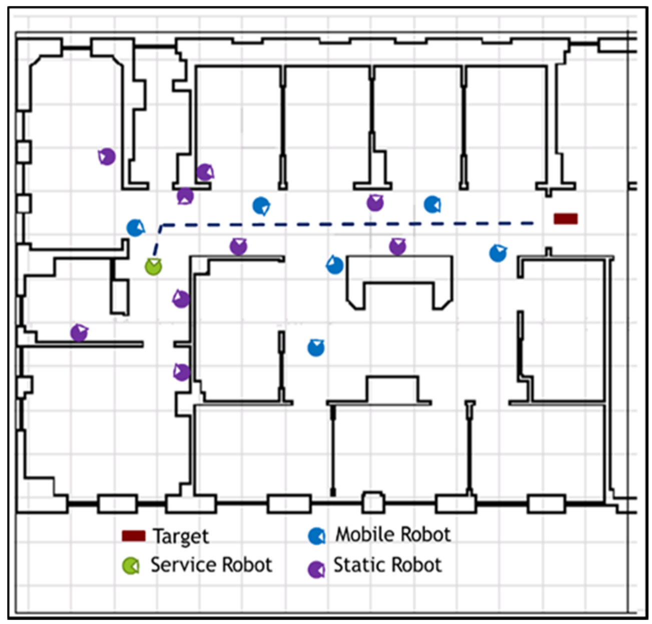


Figure 1. All mobile and static cooperate with service robot to track its target. Based on information from multiple robots, the service robot estimates the position of target and plan its path.

Here, the location of the target can be beyond the field-of-view of service robot. When service robot broadcasts its search, requests to neighbouring robots for assistance in searching for its target, the robots either send back visual confirmation on the location of the target or relay the search information to other neighbouring robots. Once the target is found, the information on position of target is then propagated back to service robot which will in turn utilize that in order to estimate the position of target with respect to its reference coordinate frame.

Despite the computational costs associated with the higher complexity in motion planning strategy, control of multiple cooperative robots through a communication framework offers a number of advantages such as increase in coverage area and reduction in levels of uncertainty in positioning the targets. In addition, other advantages may include the increase in energy efficiency in pursuit and tracking of targets when deployed.

This paper proposes a communication network protocol that propagates the search information and distribute the information associated with the target among the group of robots for cooperation navigation. The paper also demonstrates the application of our approach on an experimental set-up which further establishes the performance and feasibility of our approach. The rest of the paper is organized as follows. Related works are presented in section II. Section III describes the proposed approach and . Based on the proposed approach, the experimental setup was designed and implemented as shown in Section IV following with evaluation of the results. Section V concludes the paper along with discussion on future works.

II. RELATED WORKS

In general, multi-robot system can be represented as mobile sensor network. In order for multi sensors to efficiently carry out a given task, it is important to focus on how the sensors can collaborate to selectively aggregate multiple sources of data to improve detection accuracy [6]. For this, a set of several challenges is needed to be addressed [7] [8].

Three kinds of approaches have been adopted in cooperative localization and tracking of robots. [9] and [10]have proposed solution in estimating the position of robots in centralized framework. Centralized framework ensures complete and efficient control over the robots. On the other hand, [11] and [12] have approached the problem as decentralized network of sensors with the benefit of scalability and ease of control. However, distributed approach offers better advantage over these two approaches in large networks due to no single point of failure [13] [14]. This important characteristic would prove quite valuable for co-operative robots.

With widespread use of low cost RGB-D sensors and wireless communications, localization approaches vary in different applications as highlighted in [15] which also presents a comprehensive survey on difficulties faced in localization. One of the main challenges in localization of moving targets is to develop collaboration systems which selectively aggregate multiple sources of data to improve accuracy. [16] develops semi-definite programming (SDP) relaxation based method for the position estimation problem in wireless sensor networks. [17] introduces boot-up protocols of self-organization of energy constrained sensor networks. These protocols are scalable to large number of sensor nodes. Furthermore, [18] improved cooperative tracking protocols in order to accommodate more trackable targets by active vision sensors/agents.

[19] presents a statistical algorithm for collaborative mobile robot localization. Their approach uses a sample-based version of Markov localization, capable of localizing mobile robots. When a team of robots localize themselves in the same environment, probabilistic methods are employed to synchronize each robot's belief whenever one robot detects another. Their method can enable the robots to localize themselves faster and maintain higher accuracy. [20] describes region-based approach in multiple robot co-ordination based on target distribution and cooperative tracking of multiple targets. Also, they have addressed this problem by modelling the problem as a least squares minimization problem. They further demonstrated that the problem can be efficiently solved using sparse optimization methods.

This paper focuses on distributed approach towards cooperative localization and tracking. First we formulized the problem of target tracking by a team of robots. Then we proposed a novel cooperation method based helps each robot to recognize other robots in the team and to locate its corresponding target. The proposed method is based on QR code which nowadays are available in every places and can be created easily. Finally, we evaluate our method in a real set-up of robots.

III. PROPOSED APPROACH

In this section, we present the details of the proposed method to track target by a team of robot in a distributed manner. The general problem of target tracking by a team of robots is formulized in subsection A and then our proposed method of communication is presented in subsection B. Finally, The detail of communication method through network for positioning of robots and target is proposed in subsection C.

A. Problem Description

Consider a system with N robots $\mathcal{R} = \{R_1, R_2, R_3 \dots, R_N\}$, which can be either mobile or stationary, and M targets $\mathcal{T} = \{T_1, T_2, T_3 \dots, T_M\}$. Each robot is only equipped with a RGB-D or RGB sensor with limited field of view (FOV) and can communicate with each other through wireless network (IEEE 802.11 n). Each robot should track a certain subject as an accomplishment of its task. If the number of Task is smaller or equal to number of robots $(M \leq N)$, the generalised task allocation function for tracking M targets by N sensors can be formulated as follows.

$$TF(R_i, T_j) = \begin{cases} 1\,, & if\ tracker\ R_i\ is\ assigned\ to\ T_j \\ 0, & Otherwise \end{cases} \tag{1}$$

Equation (1) assigns one robot to track one corresponding target. Each open task should be accomplished by one robot (each subject should be tracked by a robot) which leads to equation (2) and therefore, total of M task should be accomplished (showed in equation (3)).

$$\therefore\ \sum_{i=1}^{N} TF(R_i, T_j) = 1\,, \forall T_j \in \mathcal{T} \tag{2}$$

$$i => \sum_{i=1}^{N} \sum_{j=1}^{M} TF(R_i, T_j) = M \tag{3}$$

A point to be noted is that the Task function is assumed to be given by a task allocation method which is beyond the scope of this paper. For further information on task allocation, one may refer to [21] and [22].

Let each robot observe and detect any of the target within its FOV. Such observation can be formulated by the function in equation (4) where if the robot has the j^{th} subject (T_j) in its

FoV then the output of the function is one and otherwise, is zero.

$$V_t(R_i, T_j) = \begin{cases} 1 & \mathit{if}\ T_j \mathit{is\ in\ the\ FOV\ of}\ R_i \\ 0 & \mathit{if}\ T_j \mathit{is}\ \textbf{not}\ \mathit{in\ the\ FOV\ of}\ R_i \end{cases}$$

(4)

If the task of tracking of j^{th} target (Tj) is assigned to R_i , a success function $S(R_i, T_j)$ is defined in equation (5) which shows if R_i was able to track the T_j :

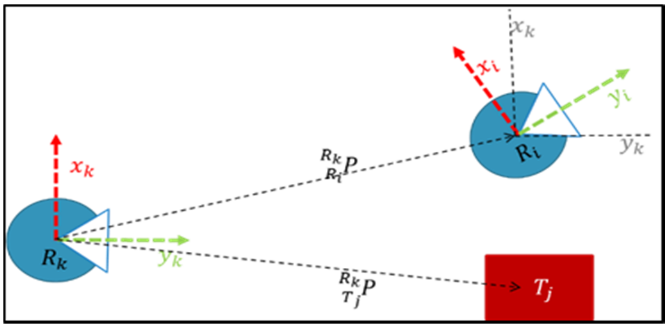


Figure 2: Frame assignment of robots

$$S(R_i, T_j) = V_t(R_i, T_j) * TF(R_i, T_j),\ S(R_i) \in \{0,1\} \qquad (5)$$

In this paper we assume a robot achieves success if it can find the assigned target to track. However, success can be defined as any other function based on the task allotted to the robot. If $S(R_i, T_j) = 0$ then the robot should search for its assigned target and if the robot is able to track its corresponding target then $S(R_i, T_j) = 1$. Finally, the success of the system can be measured as $\sum_{i=1}^{N}\sum_{j=1}^{M} S(R_i, T_j) = \mathcal{S}$. If $\mathcal{S} = M$ then the whole system is successful. All robots should cooperate (section 3, part B) with each other to guide the R_j to its corresponding task T_j (where $Tf(R_i, T_j) = 1$ (equation 1) and $S(R_i, T_j) = 1$ (equation 5)) towards T_j and thus we aim to converge $\mathcal{S} \rightarrow M$.

Despite the presence of sensor communication network, not every robot can have visual information on all targets and also on other robots. In general, only a small group of robots in the sensor network would be able to detect the target T_j. This fact is also consistent in detecting other robots. The visibility of a robot to another one is defined in equation (6) as follows.

$$V_r(R_i, R_j) = \begin{cases} 1 & \mathit{if}\ R_j \mathit{is\ in\ the\ FOV\ of}\ R_i \\ 0 & \mathit{if}\ R_j \mathit{is}\ \textbf{not}\ \mathit{in\ the\ FOV\ of}\ R_i \end{cases} i \neq j,$$

(6)

This function describes the visibility of R_j by R_i and due to limited FOV this is not necessarily commutative i.e. $V_r(R_i, R_j) \neq V_r(R_j, R_i)$. Suppose a robot R_k detects target T_j thereby $V_t(R_k, T_j) = 1$. Hence R_k should relay some information on the position of T_j to the task allocated R_i with $S(R_i, T_j) = 0$.

However, two major problems arise. First, R_k should be able to localize the position of target T_j and should communicate this information to R_i . This communication information content should be sufficient for R_i to decode the position of the target. Second, due to the fact that R_k may not be in the FOV of R_i i.e. $V_r(R_i, R_k) = 0$ then R_k should be able to pass on the proper information to other robots which handed in to R_i . To overcome these issues, a communication framework is proposed and described in the next subsection.

B. *Cooperative Localization of Neighbouring Nodes*

Each robot should be able to localized according to the relative poses of neighboring nodes (i.e. robots or target). This information can be used either for communicating this data to other robots or utilized for following the target.

Suppose robot R_k has the visual information on neighboring nodes (i.e. robots or target) and it wants to communicate its related poses to any other robots within its communication range. Within its FOV of its on-board sensor,

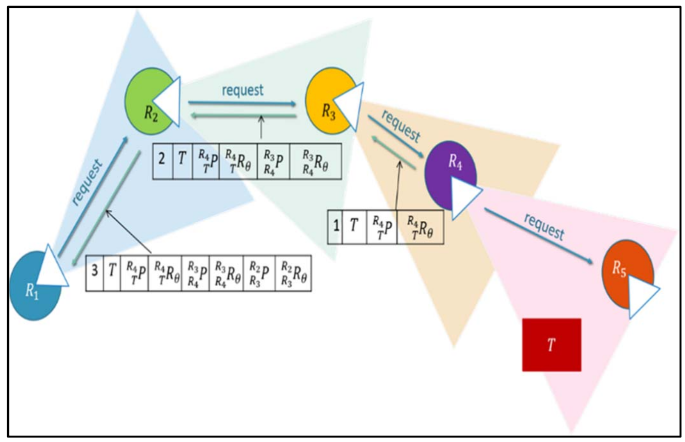


Figure 3: An example of team of robots $\{R_1, R_2, R_4, R_5\}$ cooperating with each other to help R_1 track target T.

each robot would be able to calculate the position and orientation of a neighboring nodes as detailed in Section IV.

Figure (2) depicts the frame assignment of robots. If a robot R_j is within FOV of R_k i.e. ($V_r(R_k, R_j) = 1$), R_k calculates position ${}^{R_k}_{R_j}P$ and orientation ${}^{R_k}_{R_j}R_\theta$ of R_j with respect to its frame. Four QR-code is attached to each side of each robot. Each QR code provides four pieces of information. First the ID of the robot, second the corresponding side (which could be negative or positive x or y axis) and the actual size of the actual area of QR-code and finally two specific points in the QR code. These pieces of information are utilized to calculate the orientation and the position of two robots respect to each other.

On the other hand, only position ${}^{R_k}_{T_j}P$ of T_j in the frame of R_k would be calculated by R_k when $V_t(R_k, T_j) = 1$. If $TF(R_k, T_j) = 1$, R_k will follow T_j. If not, then R_k will send the information containing ${}^{R_k}_{T_j}P$ to other neighbouring robots till that information reaches the robot (say R_i which is responsible to track T_j) whose $TF(R_i, T_j)$=0. As the information passes through robots, each robot R_k at each hop will add position

${}^{R_k}_{R_j}P$ and orientation ${}^{R_k}_{R_j}R_\theta$ of previous robot R_j and broadcast to nearby robots if $V_r(R_k, R_j) = 1$.

C. Indoor Positioning Network

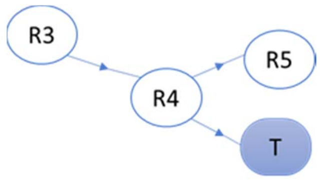


Figure 4: Corresponding partial network graph from Table 1.

Figure (3) shows the conceptual illustration for cooperative localization of targets and robots. In the proposed communication protocol, each robot in the sensor network needs to update its defined neighbourhood visibility table to store information relative poses of neighbourhood nodes as shown in Table 1. This table stored in each robot memory is utilized to generate partial graph of visibility for each root. Figure (4) illustrates the partial graph generated using Table 1. Each robot have a unique ID to be distinguishable with others. The table contains the ID of the neighboring node with its corresponding relative position and orientation.

Within sensor network of robots in Figure (3), a robot R_1, whose task function $TF(R_1, T)$=1, has to follow and track assigned target T. However, according to Figure (3), T is beyond the FOV of R_1, i.e $S(R_1, T) = 0$. So R_1 broadcasts $\boldsymbol{request}$ message containing ID of T and R_1 to neighbouring robot R_2. However, R_2 doesn't have visual information on T in its neighbourhood visibility table. So, R_2 broadcast the message to other nearby robot R_3. Since R_3 also doesn't have visual information on T, it broadcasts the same request to next nearby robot R_4.

Finally, R_4 has visual information on target T according to its neighbourhood table in Table 1. Hence, it broadcasts back $\boldsymbol{found}$ message, illustrated in Figure (3), to nearby robots within its communication range. An important point to be noted that not all robots within communication range of a robot will be in the visibility range of the robot. Since R_3 is within communication range of R_4, it receives that $found$ message. If $V_r(R_3, R_4)$=1, R_3 updates the $found$ message and the field containing the number of robots in middle, as illustrated in Figure (3). The process continues till the $found$ message has

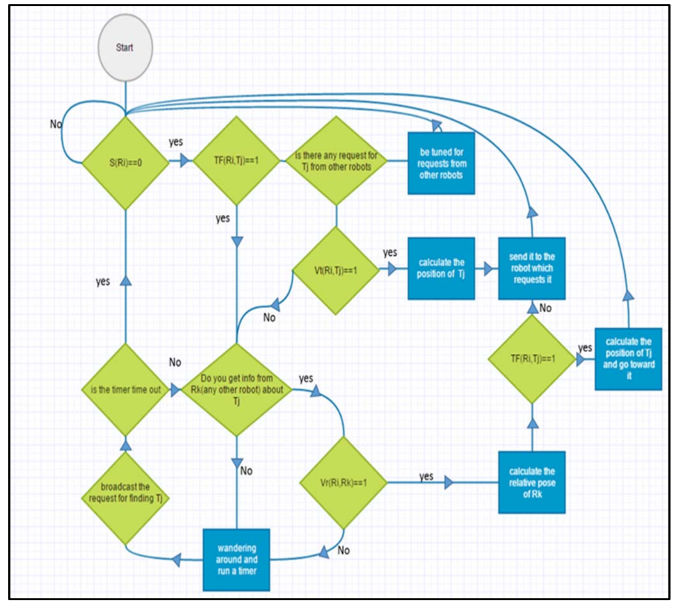


Figure 6: The flowchart of the proposed algorithm

received to R_1. Since R_1 is looking for target T and the message contains ID of target T, the robot read the data to find it. Figure (5) shows the behavior of the robot when it receives a message. Eventually, R_1will be able to estimate the position of target T and calculates the relative position (${}^{R_1}_{R_2}P$) and orientation (${}^{R_1}_{R_2}R_\theta$) of R_2. Figure (6) shows the flowchart of the proposed algorithm for the whole system. This algorithm would be run in each robot R_i independently. Each robot needs to run the program for each target T_j simultaneously.

IV. Experimental Results

The proposed algorithm was evaluated in a real-time hardware experimental setup to assess the efficiency and robustness of the proposed algorithm.

A. Experimental setup

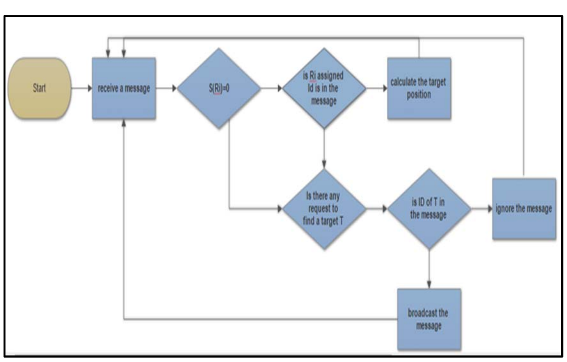


Figure 5: The behavior of the robot when it receives a message

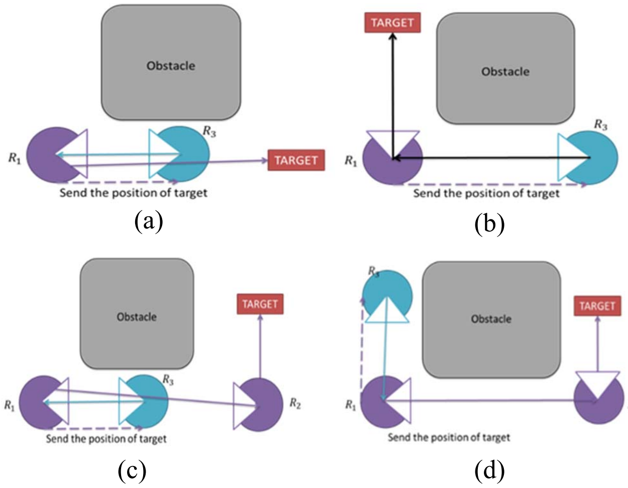


Figure 8: Four scenarios for evaluating the proposed algorithm. Blue circle indicates the robot in charge. Purple circles are the other robots present in the environment. a) First scenario b) Second scenario c) Third scenario d) Forth scenario

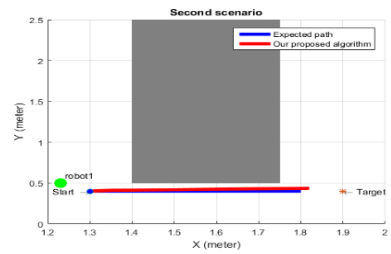
For the setup, a mobile Oculus Prime robot [23] and two stationary Microsoft Kinect V2 sensors were used as shown in Figure (7). Four QR codes were attached to each sensor and the mobile robot. These codes can be easily generated from online websites as [24], [25]. In this paper, we also proposed using a simple QR code not only as ID but also as a key component of localization function. Each QR code contains the ID of the sensor and the corresponding axis. Thus, the robot can extract the rotation matrix (i.e. ${}^{R_i}_{R_j}R$) after identifying and deciphering the QR codes. Also, the relative position of two sensors or the mobile robot ${}^{R_i}_{R_j}P$ is calculated by knowing an approximate size of the attached QR codes. We estimate the intrinsic parameters of the RGB camera of the mobile robot and sensors by the checker board method. Then, we use Pinhole camera model [26] to estimate the distance between each of sensors and the mobile robot (i.e. ${}^{R_i}_{R_j}P$). Finally, the robot moves towards other sensors to find the target and accomplish its task.

B. Evaluation results

To evaluate our proposed algorithm, we define four different scenarios. In all scenarios, we assume that that robot R_3, which is responsible for tracking the target T which cannot be seen (i.e. $TF(R_3, T) = 1 \; and \; S(R_3) = 0$). Also, R_1 and R_2 acts as co-operative sensor robots.

In the first and second scenarios, R_2 can detect the target and sends the target's information to $R_3(Vr(R_3, R_2) = 1, Vt(R_2, T) = 1\,)$. In the third and fourth scenarios, we assume that R_1 can identify the target and send this data to R_2. Once R_2 has received the visual confirmation on T from R_1, it relays that information to R_3. Based on that information, R_3 finally plans its path toward the target. It should be mentioned that we define a period (say $0.5s$) in which R_3 updates the information about the target. Finally, R_3 continue its path toward the target.

Each scenario was evaluated in ten trials. Due to uncertainty of the environment and the robot hardware, there would be a slight difference in performance for each run of the scenario. All four such scenarios with corresponding evaluations have been depicted in Figure (8) and Figure (9) respectively. We expect a defined path for each scenario based on the environment map and the position of R_3.



a)

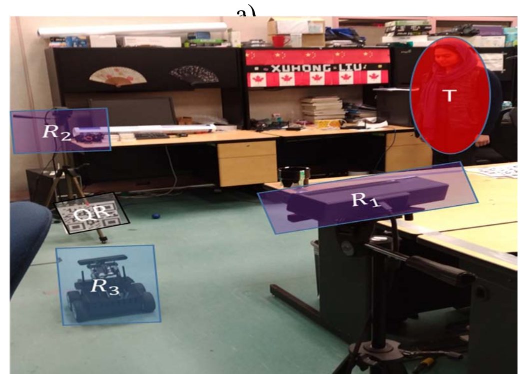
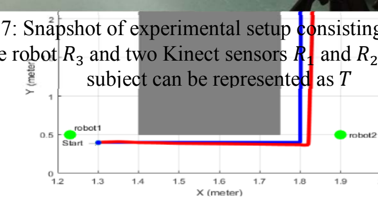
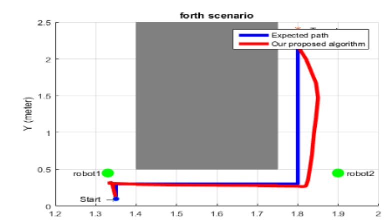


Figure 7: Snapshot of experimental setup consisting of the oculus prime robot R_3 and two Kinect sensors R_1 and R_2 . The target subject can be represented as T



c)



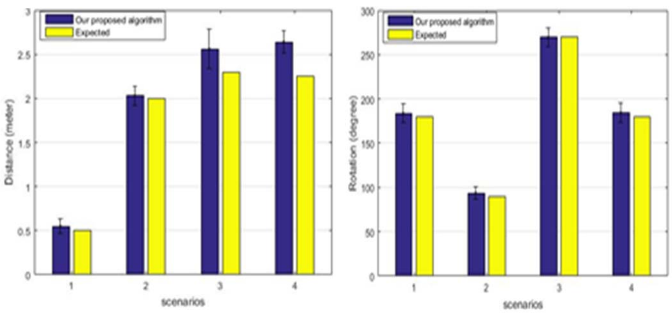
d)

Figure 9: The expected path and a sample behaviour of the robot using proposed algorithm a) First scenario b) Second scenario c) Third scenario d) Forth scenario

In the first scenario (Figure (8a)), we expect R_3 to rotate 180 degrees and go towards the target. In Figure (8b), the robot should first rotate 90 degrees and then go towards the target. For the third scenario (Figure (8c)), the robot should rotate 180 degrees, move R_2, rotate 90 degrees, and go towards the target. Finally, in the last scenario (Figure (8d)), R_3 should rotate 90 degrees and go toward R_1 and turn another 90 degrees and go towards the target T.

Figure (9) shows a sample data of one of trails for each scenario. It compares the robot's movements in the trial with expected path. The expected path is the shortest path taken by the robot R_3 to achieve the target. As you can see, R_3 finds the target successfully and its path is quite close to the expected path.

The commands sent to the robot R_3 are divided into two



(a) (b)

Figure 10: The average of a) movement b) rotation using the proposed algorithm against the expected path

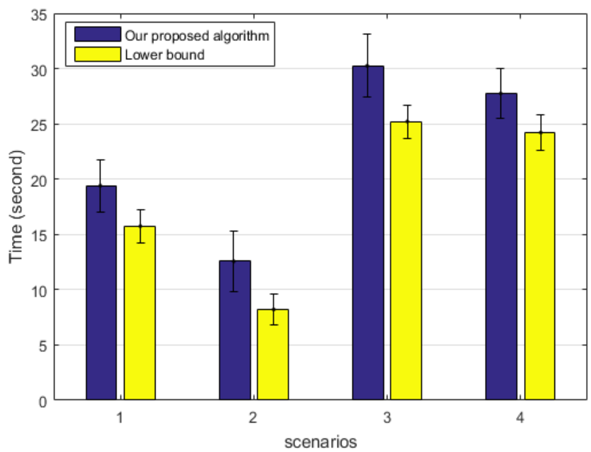


Figure 11: Average time taken to accomplish the task across all sceraio runs

groups: rotations and movements. For each type of commands, we measure how accurate the robot can approach the expected (desired) values. The mean and standard deviation of rotation and movement are shown in Figure (10) and compared to expected movement and rotation.

If the robot knew the position of the target in advance, it would directly move towards the target avoiding extra communications with other robots present in the environment. For evaluation of our proposed approach as presented in Figure (11), the expected task accomplishment time for robot R_3 for each scenario was set as a lower bound for our proposed algorithm. Also, the lower bound was obtained and set for each of 10 trails. From Figure (11), the overall average time difference from ideal task accomplishment for all scenarios in all 10 trails was found to be 4s. In both scenarios 3 and 4, the average time taken for robot to reach its target would be higher as compared to other scenarios 1 and 2.

V. DISCUSSIONS AND CONCLUSION

In this paper, a distributed cooperative localization and tracking framework was proposed. Also, the flow of localization information among the robots was described. The proposed approach was successfully implemented in a small group of robots. In addition, it was also successfully evaluated with the average time difference between the ideal time and proposed algorithm's process time taken for robot to reach its target as 4s. Our method works with a lowest equipment. In fact, all the process is done in a fully distributed manner and the QR codes were utilized for both ID assignment and localization.

For our future work, we plan to implement the method on a larger network of robot and multiple targets in the environment. For a large sensor network, each robot will bound to receive information on position of multiple targets from multiple sources. Each robot will only choose the information of its target according its task allocation function. If the information of that target comes from multiple sources (Figure 11), the robot could then estimate the position of its assigned target more accurately. It can either average the estimates of position of target or filter those estimates using Kalman filter [27] or particle filter [28].

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