Designing a Reliable Fiducial Marker Network for Autonomous Indoor Robot Navigation

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Abstract –

Automation and robotics offer significant potential to address some of the challenges faced by facility managers to efficiently operate and maintain indoor building environments. Previous efforts have focused on deploying mobile service robots for scheduled and periodic tasks such as monitoring, inspecting, and collecting data. Localization and navigation are two of the fundamental capabilities required for any robotic system to accomplish these periodic tasks successfully. Most of the existing approaches for achieving semi/fully autonomous indoor mobile robot navigation either require dense instrumentation of the physical space (e.g., Bluetooth beacons) or are computationally burdensome (e.g., Simultaneous Localization And Mapping). To address these issues, the authors previously developed localization, navigation, and drift correction algorithms based on cost-effective and easily-reconfigurable fiducial markers (e.g., AprilTags). However, these algorithms were based on context-specific assumptions regarding the marker characteristics, sensor capabilities, and environmental conditions. This study comprehensively investigates the design characteristics of a fiducial marker network localization system to achieve autonomous mobile indoor navigation. A generalized framework in the form of a process flow chart is proposed that is agnostic of indoor building environment application, marker category, robot, and facility type. That is, the proposed framework can be used to systematically to design the desired robot, required sensors, and create the optimal marker network map. The feasibility of the proposed approach is explained with the help of a facility management related example. The outcomes of this study can be generally applicable to any mobile robot, building type (e.g., office), and application (e.g., construction progress monitoring).

Keywords –

Autonomous Robot Navigation; Fiducial Markers; Indoor Localization; and Facility Management

1 Introduction

Recent advancements in technology have given rise to the use of intelligent robots for several service applications. Some of the examples of deployed indoor robotic systems for professional and domestic service applications include museum guide robots [1], hotel butler robots [2], vacuum cleaning robots [3], and surveillance robots [4]. As per a report published by the International Federation of Robotics in 2018, the annual growth rate in service robots is about 21% [5]. In addition, Baeg et al. [6] emphasized the significance, usability, and the potential of service robots for everyday activities. It can thus be reasoned that intelligent robots will soon be ubiquitous and there is a strong need to explore the potential of robots to improve autonomy in the operation and utilization of today's buildings.

Two of the fundamental capabilities robots need to possess to enable such autonomy are localization (i.e. identify and orient their location in the physical environment) and navigation (i.e. direct to the respective locations of interest). Previous approaches and methods either require dense instrumentation (e.g., bluetooth beacons) of the physical environment (i.e., significant upfront costs, suffer from low accuracy (e.g., wireless local area network), or made application-specific assumptions (e.g., marker-based systems). To address the limitations of existing studies, the authors propose a general framework for marker-based localization and navigation systems in the form of a process flowchart that is agnostic of the indoor building environment application, marker category, robotic platform, and facility type. The proposed framework is general, not domain specific, and can be used for several single and swarm indoor robotic system applications. The use and feasibility of the proposed framework are illustrated with the help of several built environment examples.

In the context of this paper, localization is defined as the robot's ability to identify its current location in a given indoor environment setting [7]. For example, a robot being able to recognize that its location is in room 201, or knowing its location and orientation in the global coordinate reference system. The robot's navigation can be briefly defined as the robot's ability to plan a course of action to reach the destination location while accurately localizing itself in its frame of reference at strategic locations [7].

Several indoor localization and navigation techniques have been explored previously. Literature suggests that every method has advantages and limitations. Some of the previous approaches explored for robot localization include Wireless Local Area Network (WLAN), Ultra-Wide Band (UWB), Bluetooth, Cameras, and Lasers. Wi-Fi is an economical solution because most of the existing infrastructure consists of wireless nodes required for localization. However, it suffers from a significant error in localization accuracy [8,9]. Bluetooth based localization tends to be expensive, time-consuming and also have space constraints because of the requirement of wireless infrastructure deployment indoors [8,10]. Similarly, UWB-based systems require a large number of receivers making it inconvenient and infeasible (due to space constraints) indoors [11,12].

Laser scanner based techniques eliminate the need to instrument the physical space but they are highly expensive, sensitive to obstructions and require high computational capabilities [1,13-17]. To summarize, common disadvantages affecting a majority of the reviewed methods include low accuracy, significant upfront investments, high computational requirements and complex instrumentation of the indoor environment.

Vision-based methods using fiducial or natural markers are particularly immune to the disadvantages mentioned above. This is because, markers offer high accuracy in estimating the relative three-dimensional pose in an environment, require relatively less computing capabilities, are cost-effective, and are easy to install [18-20]. In addition, fiducial markers can store virtual information regarding a multitude of things such as information regarding physical location (e.g., room number), emergency evacuation directions, indoor navigational information, and inspection-related data regarding building systems helpful for facility managers [14]. Feng and Kamat [14] demonstrated how markers having virtual information and navigational directions can help humans navigate indoors.

To take this further, Mantha et al. [21] showed that the virtual location information (for localization), navigational direction (for navigation), and 3D pose estimates (for drift correction) can be used to achieve autonomous behavior of the mobile robot. However, this was just a proof of concept which used a specific type of robotic platform, camera, marker type, marker size, and facility type which cannot be generally applicable to other scenarios or built environment applications.

1.1 Importance of the Research

Robots have become increasingly pervasive in our day to day lives, with global experts predicting that intelligent robots will soon be ubiquitous [22]. Baeg et al. [6] emphasized the usability of service robots for everyday activities. Building Service Robots have numerous advantages such as a) high productivity: can perform tasks significantly faster without getting tired (e.g., laying bricks) [23], b) improve safety: can work in harsh and unsafe environments where humans are unwilling or unable to work (e.g., gas pipe inspection) [24], c) reduce cost: cheaper than human counter parts (e.g., it is very cheap to deliver items in hospitals/hotels with robots) [2, 25], d) improve quality: robots can be more precise and accurate than humans (e.g., structural monitoring) [24], e) provide better quality of life: can help the people with restricted mobility or handicaps with several mundane tasks (e.g., help blind people navigate indoors) [26]. The demand for Building Service Robots is also reflected in the exponential increase in the venture capital investment in robotics [27]. More importantly, the world robotics executive summary released in 2016 estimates around 23 billion USD in sales for the professional service robot installations between 2016 and 2019. In addition, a study published by McKinsey shows that the price of these robotics systems continues to drop (almost halved), whereas, the labor costs have consistently increased [28].

Thus, there is a strong need to investigate the potential of these systems, especially for facility management applications. Most of the existing service robotic systems still rely on expensive sensors, computationally intensive methodologies and complex instrumentation for semi and fully autonomous navigation. In addition, these systems are particularly disadvantageous for temporary or one-time applications such as air quality assessment, retrofit decision making, occupant schedule detection, and structural health monitoring [21]. On the contrary, marker-based systems offer significant potential since they are easily reconfigurable, cost-effective (can be printed on paper), and computationally efficient [14].

Different types of markers have been developed and studied in the recent past. For example, Xu and McCloskey [29] developed a 2D barcode-based localization system. Though this is an economical solution when compared to the previous alternatives, 2D systems fail to provide 3D orientation information. This is particularly important for successful indoor robot navigation. Olson [20] developed AprilTags that can be printed on a regular paper but have the capability to determine 3D relative pose information.

Feng and Kamat [14] used these markers for indoor wayfinding applications. Furthermore, Babinec et al. [19] showed how a mobile robot can be localized using planar markers. Extending this further, Mantha et al. [21] used these markers for mobile robot navigation. However, all these aforementioned methods were just proof of concepts with context-specific assumptions regarding marker size, marker placement, and camera type. On the other hand, several other studies focused on improving individual marker characteristics such as successful detection rate, performance of the detection algorithm, size of the marker, and camera configurations. For example, Romero-Ramirez et al. [18] compared the speed performance of detecting different markers such as ArUco, Chili tags, AprilTags, and ArToolKit+. Lundeen et al. [30] compared the accuracy performance of different marker sizes, relative marker camera distances, and its relevance to the operation of an autonomous robotic excavator. However, none of the aforementioned studies, nor other existing studies, integrate, investigate, and identify the appropriate selection of marker networks for autonomous indoor robot navigation. That is, none of these studies establish a procedure to determine the optimal marker network design characteristics (e.g., marker camera configurations) based on a given set of inputs (e.g., facility type, and application objectives).

Thus, the objective of this research is to develop a general framework that can be used by facility managers or stakeholders to identify optimal camera marker network design characteristics based on different inputs (e.g., application objectives). The proposed framework is applicable to single or multiple robotic systems with and without constraints such as performance speed, occlusions, and lighting conditions. The feasibility of the proposed framework is explained in detail with the help of a facility management related example involving a variety of robotic platforms and marker types.

2 Proposed Framework

The framework is divided based on four main roles namely facility manager, real building, robot, and markers of the whole camera marker network design process for the autonomous robotic navigation. Each of these directly or indirectly influence, possess or are responsible for certain tasks and/or actions. Figure 1 shows the proposed framework including each of the aforementioned roles, their tasks, actions, processes, and sub processes. The different tasks of the proposed framework are illustrated using the example of ambient robotic data collection presented by Mantha et al. [21]. It has to be noted that for simplicity and easier understanding of the reader, tasks are described as sub sections of each role rather than in the chronological order of the process flow shown in Figure 1.

2.1 Facility Manager

One of the important roles of this framework is the facility manager who is responsible to define the objectives pertaining to the application context and the corresponding inputs. The objectives can be derived from the targeted action or intended tasks that need to be performed. In the example considered, the objective is to monitor ambient parameters in buildings. Therefore, the intended action is to gather data regarding ambient parameters such as temperature, relative humidity, and lighting, and compare it with the standard parameter range or the occupant preferences. Other relevant inputs can be the locations in the building and the frequency at which the data needs to be collected.

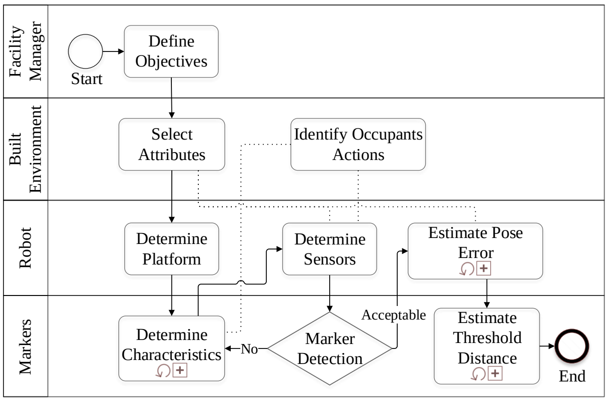

Figure 1. Design of marker network map for autonomous indoor robotic navigation.

2.2 Built Environment

Service robotic systems are designed to navigate in the built environment and perform the assigned tasks. Hence the built environmental attributes along with the users (or occupants) actions will significantly influence the design parameters of the robotic navigation system (marker network system in the context of this paper). Each of these categories is described below in detail.

2.2.1 Select Attributes

Attributes primarily represent the physical properties and characteristics of the built environment such as facility type, floor plans, equipment, surface geometry, flooring type, thermal zones, lighting, acoustics, and other services. In the previous ambient parameter monitoring example discussed at the beginning of section 4, some of the relevant attributes can be indoor temperature, relative humidity, light intensity, sound levels, and indoor air quality.

2.2.2 Identify Occupants Actions

Occupants are users of the built environment who directly or indirectly interact with the robotic systems. Though this task is not part of a technical process flow as can be seen in Figure 1, this can impact the characteristics of the markers (i.e., marker placement in particular) and determination of sensors (e.g., camera in this case) on the robot. Thus, identifying occupant actions is important as they have the potential to impact the successful accomplishment of the goals and objectives. Some examples of the behaviors and actions of the occupants include their movement, schedule, use of the built environment, and routine. In the example case considered, occlusions due to occupant movement and their interaction with these systems to provide feedback in the form of a questionnaire regarding their preferences are some of the most important factors to be considered. Further details regarding the significance of occlusions is described in the marker placement section of this paper.

2.3 Robot

In the context of this paper, three important tasks that encompass the role of an indoor robot are the type of platform, sensors (e.g., camera for detecting markers), and navigation performance (e.g., error accumulation). Though other elements such as task allocation, path planning, and motion planning for task execution are critical, they are not considered in the scope of this study and hence are not elaborated. However, interested readers are referred to [30,31] for further information.

One of the other considerations which did not receive much attention in the past is the cybersecurity implications of these intelligent autonomous agents [32]. This is particularly important in this case because of the potential human-robot collaboration and the accessibility of these robotic systems in these facilities. It has to be noted that the cyber threats are not just limited to data breaches but can cause some serious safety concerns to the infrastructure and the occupants [33,34]. So, with the increasing popularity of artificial intelligence enabled autonomous mobile robots, it is necessary to keep a check on the cybersecurity aspects, safety standards, and risk assessment of the robot chosen.

2.3.1 Determine Platform

As the name suggests, the goal of this step is to determine the ideal robotic platform based on the defined objectives (refer to section 4.1). The classification of robots can be dependent on several things such as the type of work, mechanical structure, or morphology [35]. Here, the goal is to determine the mechanical structure of the robot whether it is a mobile robot with wheels, legs, wings, tracks, or any other existing automated platform. In the example application, since the mobile robot needs to collect data and get occupant feedback, a mobile robot with wheels and a display platform for interaction might be ideal. Though a legged locomotion-based robot might also serve the purpose, a mobile robot with wheels might outpace the legged robots and can be more efficient (faster) in collecting data.

2.3.2 Determine Sensors

Though several sensors will be required on the robot, in the context of this paper, the sensor (camera) for the purpose of localization and pose estimation is discussed. One of the advantages of marker-based pose estimation systems is that they do not require expensive cameras. The type of cameras available on mobile phones these days can be used. Typically, most of the robotic systems come with a built-in camera. These cameras are of sufficient quality to be used for the purpose of marker-based localization and pose estimation [18].

2.3.3 Estimate Pose Error

One of the most important factors that have a direct impact on whether the robot will successfully navigate to desired locations or not, is the relative pose error accumulation of the robot. This is because there is always a difference between the robot's actual and ideal pose. It is important to estimate this at regular intervals and rectify it accordingly. Relative pose between camera and marker can be determined by a total of six components, three of which correspond to translation (e.g., x, y, and z) and three of which correspond to the rotation (e.g., roll, pitch, and yaw angles). This is represented in the form of a homogenous transformation matrix (H) in which R (3*3) denotes a rotation matrix and T (3*1) denotes a translation matrix (Eq. 1). However, depending on the type of application, only some of these six components might be required. For example, in case of ambient data collection, only the lateral distance (distance between the camera and the marker) is extracted and hence the pose error is estimated only using the variance of this parameter with respect to the ground truth values.

$$H = \begin{matrix} R11 & R12 & R13 & Tx \\ R21 & R22 & R23 & Ty \\ R31 & R32 & R33 & Tz \end{matrix} \tag{1}$$

Where,
H is part of the Homogeneous transform matrix
R (3∗3): Rotation matrix
T (3∗1): Translation matrix

A generalized procedure of the sub process for estimating the pose error is shown in Figure 2. First, assume a zero yaw angle (as shown in Figure 3) and determine the camera marker distance range. That is, the minimum and maximum lateral distance between the marker and the camera (i.e., robot) to be able to detect the marker. Then, identify the ideal marker to camera distance to maximize the allowable error accumulation based on the environmental attributes and robotic platform. Further discussion regarding the reason for maximizing the allowable error is provided in section 4.4.3. If further optimization is required for the pose error, relative camera marker orientation can be varied to achieve the same. Though it might seem counter-intuitive, it is possible that a non-zero yaw angle (e.g. -15 degrees) gives better results than a zero yaw angle [30].

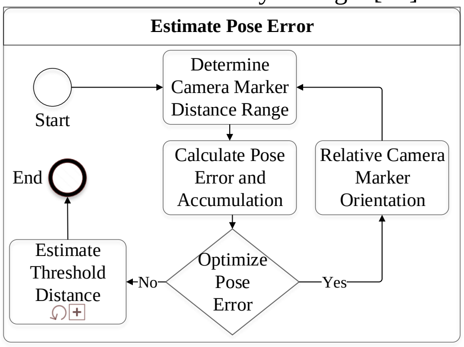

Figure 2. Sub-process to estimate pose error

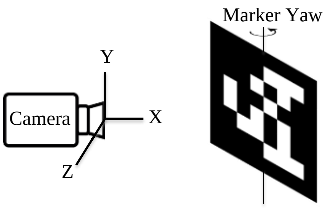

Figure 3. An illustration of marker yaw

For example, in the case of ambient robotic data collection, the robot's ideal path is along the centerline of the corridor to maximize allowable drift as shown in Figure 4. This is because, if the robot's ideal path is closer to the wall, the allowable drift accumulation will be very less (compared to the robot's path being on the centerline of the corridor) to avoid the robot colliding with the wall. The allowable drift accumulation, in this case, will be less than half the width of the corridor considering the width of the robot.

2.4 Markers

A fiducial marker is an artificial landmark with prescribed geometry and features to distinguish itself from the naturally occurring objects and other markers. The detection is usually done by capturing videos of markers using optical cameras and subsequently analyzing the image to determine the relative camera marker pose [30].

Unique fiducial markers are required to be placed at strategic locations along the navigational path of the robot (e.g., corridors, entrances to rooms, etc.) to form a Marker Network Map (MNM). These markers will act as landmarks, and the strategic locations can be the end of the corridors, the intersection of hallways, and entrances to the rooms. A graphical network G = {N, E} can then be generated where N represents nodes representing locations of markers and E represents edge links connecting these nodes (e.g., corridors and stairs). The network formed henceforth can be used to determine the optimal paths in the building and subsequently for the autonomous navigation of the robots. The subsections below provide further discussion regarding different marker characteristics (e.g., type and placement), detection of markers (e.g., placement), and threshold marker distance (i.e., maximum distance between two consecutive markers).

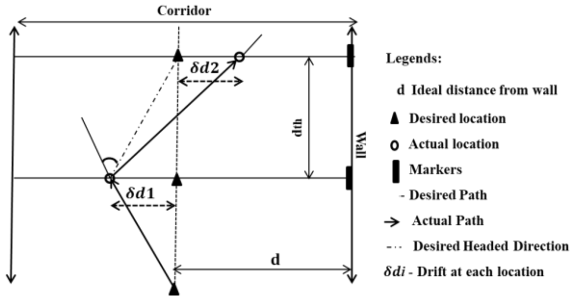

Figure 4. Illustration of drift accumulation and marker to marker distance for an indoor mobile robot (adapted from [21])

2.4.1 Determine Characteristics

At this stage, the building attributes are known and the robotic platform was chosen. This section describes the selection process for different marker characteristics.

Type, Size, and Library Size

One of the significant factors that drive the selection of the marker type and size is the error tolerance range and the type of pose requirements for the intended application based on the identified objectives. Several different types of markers were developed and studied by researchers such as planar markers, 2D bar codes, ARToolKit, BinARyID, AprilTags, ArUco, and ChiliTags [18,20,36,37]. Some of these markers are shown in Figure 5. Based on the accuracy, detection, and library sizes, ArUco and AprilTags are currently the best for marker detection [18,30].

The marker library (or dictionary) size is the number of unique markers available in chosen given marker type. For example, AprilTags have more than 4,000 unique codes, whereas ARTags have about 2,000 [20]. Therefore, it is important to check for the size of the library for the chosen marker to ensure that it meets the corresponding application before proceeding further (Figure 6). That is, estimate the number of unique markers required for the type of application and compare it with the available marker size. For example, in the monitoring example, the number of unique markers is approximately equal to the number of distinct notable locations (e.g., in front of a room, end of the corridors, and elevators) along with other possible places where data needs to be collected inside the building.

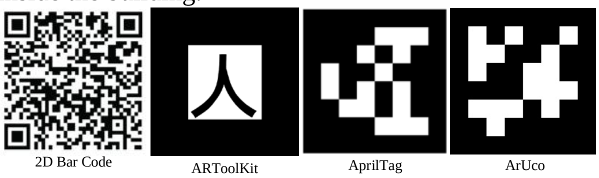

Figure 5. Different types of markers

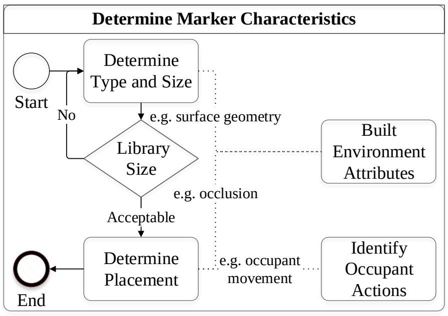

Figure 6. Sub process to determine marker characteristics

In addition, some of the built environment attributes such as surface geometry can influence the marker type and size selection. For example, if the built environment does not have planar surfaces, then larger size planar markers cannot be used because of field-of-view issues in the detection of the markers. In the ambient data collection example, the facility type is buildings with mostly planar surfaces, limited number of locations, and require relative 3D pose requirements. Thus, it is reasonable to assume that AprilTags are suitable because they are planar markers, have a decent library size, and can be used for determining 3D relative pose [20].

Placement

Different marker placement techniques such as wall mounted, ceiling mounted, and floor mounted have been explored for built environment settings [21,38,39]. However, it has to be noted that each of these methods has their own advantages and disadvantages depending on the built environment attributes such as ceiling heights, occlusions, and occupant actions such as occupant movement.

Floor mounted markers have shown promising results in a structured industrial/warehouse setting where Kiva robots manage the entire storage area of the warehouse [39]. Horan et al. [40] used a tape-based path sensing method for mobile indoor robot navigation. A similar study was performed by the National Institute of Standards and Technology (NIST), in which additional boundary markers were introduced along with the tape line [38]. However, the aforementioned floor based marker mounting techniques would suffer from frequent wear and tear in an unstructured building environment with frequent occupant movement. Ceiling mounted marker-based techniques were explored in warehouses as an alternative to the laser triangulation method [38]. However, in the context of ambient data collection, Mantha et al. [21] suggested that the ceiling heights (especially near the atrium areas) might have a significant effect on the pose estimation of the robot. Hence a wall mounted technique is ideal in this scenario or a combination of wall and ceiling mounted if multiple cameras placed on the robot.

2.4.2 Marker Detection

The immediate next step after selecting the marker characteristics is to develop a corresponding marker detection algorithm. In general terms, the marker detection algorithm works as follows. First, images are captured at a very high rate and are analyzed for the presence of a marker. This process is called segmenting. Second, the computer decodes the information from the markers in the form of 1s and 0s and determines the unique identification of the marker by cross-referencing (matching) with the library of markers. Further details regarding the detection algorithm can be found in [14,18].

Two of the important factors to be considered in the marker detection are false positive and false negative rates. False positive rate implies the rate of falsely reporting the existence of a marker in the captured image when there is no marker present in reality. On the contrary, false negative implies that there is a marker present in the image but the algorithm does not detect the maker. It is particularly important to check these rates before finalizing the marker type and size. Though the comparison of rates sometimes depends on the library size, an acceptable rate can be anything less than 0.1% [20,42]. If these rates are not acceptable, it is recommended to alter the aforementioned categories until desired results are obtained.

2.4.3 Estimate Threshold Distance

At this stage, the robot's camera can detect markers (landmarks), localize itself in the built environment, and navigate based on the relative pose. Since there will be errors accumulated along the navigational path as discussed previously (for e.g., as shown in Figure 4), it is necessary to place the markers at strategic locations to rectify the errors and ensure the robot reaches its next intended destination without drifting too much (e.g., colliding with the wall as shown in Figure 4). So, in addition to placing markers at the locations of interest, additional markers need to be placed along the way.

The objective of this specific task is to determine the threshold distance (d_{th}) between any two successive markers. That is, determine the maximum distance between two consecutive markers along the navigational path of the robot. This is a result of the maximum allowable drift of the robot and hence a direct measure of the camera marker distance and drift accumulation pattern of the robot. To calculate the threshold distance, several robot runs should be performed to estimate the distance the robot will travel with an allowable drift (less than or equal to the maximum possible drift). The threshold distance is the minimum of these distances travelled for that particular case. Figure 7 shows the representative flowchart of the sub-process estimate threshold distance. This is subject to change depending on different factors such as flooring type (e.g. wheeled robot) and payload (e.g. drones). It has to be noted that the density of the markers and threshold marker to marker distance are inversely proportional. The density of the markers is basically the number of markers per area (e..g., m^2) or length (e.g., running meter). So, higher the threshold distance, lesser the density.

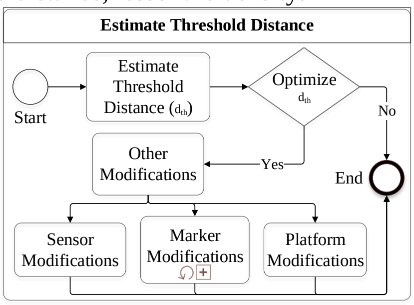

Figure 7. Sub process to estimate threshold distance

If d_{th} needs to be optimized, then the following modifications to the existing system such as a) sensors (on robot), b) markers, and c) platform (robot) can be explored. For example, multiple cameras (e.g. pointing in different directions as shown in [43]) instead of a single camera can be used to overcome occlusions and avoid more frequent placement of markers. 3D markers (i.e., multiple planar markers in the shape of a book used as a benchmark marker in [43]) can also be explored to improve visibility, optimize pose error, and subsequently optimize threshold distance. Further to that, multiple small markers instead of a single big marker can also be used to achieve the same. Finally, platform changes (e.g., other wheel types) can also be explored to optimize the error accumulation and hence d_{th}.

3 Conclusions and Future Work

A generalized framework to design a reliable fiducial marker network for autonomous indoor robotic navigation is proposed. The framework is general and can be applied to different robotic platforms operating in the built environment. Four key roles affecting the design process such as facility manager, built environment, robot, and markers are identified. The corresponding tasks and actions by these key roles that influence the marker network design characteristics such as marker type, size, library size, environmental attributes, occupant actions, robotic platform, camera marker configurations, threshold marker to marker distance are established and described in detail. In addition, four process flow diagrams are proposed that describe a step by step procedure of the proposed theoretical framework. The feasibility of the proposed framework is explained with the help of a real-world built environment example. That is by relating each of the integral task elements in the framework with an autonomous mobile robotic data collection case study. Future work aims to design two different marker network systems using AprilTags and ArUco for autonomous navigation of a specific robotic platform (e.g. Turtlebot3) in a real-world setting. The objective is to compare and analyze different design and performance factors such as threshold distance, marker density, error accumulation, optimal camera and marker configurations. Results of this study are generally applicable to any indoor robot, building type (e.g., office, retail), and application (e.g., environmental data collection). Other potential applications include construction progress monitoring, on-site worker safety identification, and real-time inventory management.

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