Adaptive Node Placement for Improving Localization Accuracy in Clutter-Prone Environments

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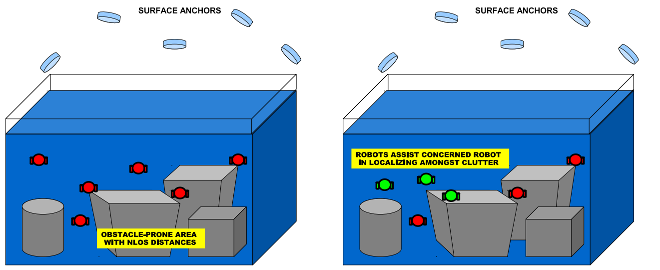
***Abstract*—Range-based localization techniques can yield unacceptably large errors when used in cluttered environments. Clutter in the environment leads to large distance measurement errors due to non-line-of-sight (NLOS) signal propagation. In this paper, we focus on the localization of a mobile node in clutter using a multi-hop localization method, namely DV-Distance, and suggest that node mobility is key to improving localization accuracy in cluttered environments. We propose APDV, a distributed control algorithm that carefully moves nodes in the monitored area to reduce distance overestimates caused by clutter and network sparsity. We evaluate the performance of APDV in simulated and real network settings. Our technique is shown to outperform existing approaches when a majority of the distance measurements are NLOS in nature.**

I. Introduction

Range-based localization is a popular, low-cost method of localization in wireless sensor robot and robotic networks (WSRNs), which entails taking distance measurements between a sensor robot and a number of anchors, special purpose nodes with known positions. However, localization accuracy is severely debilitated in the presence of obstacles between the anchors and the unlocalized sensor. The reason is the occurrence of reflected non-line-of-sight (NLOS) distance measurements. The large positive biases of NLOS distances typically result in even larger localization errors.

Robot exploration in cluttered environments is a very pertinent application of modern technology [8], [4], [9]. Here, a swarm of robots are tasked with exploring and detecting interesting phenomenon in difficult environments. The robots use beacons, that are typically situated outside the cluttered environment, to purposes of localization and reported gathered data back to a central base-station. When a robot comes across an interesting phenomena, for example, an unusually high radioactivity reading when monitoring a nuclear waste storage pond. At this stage it is vital the robot is able to determine its position accurately in order for the location of the reading to be reported. Another application is in emergency search and rescue situations where a robot can be abruptly deployed, without any prior location information (known as the kidnapped robot problem [2]).

Two options are available for robot localization in such scenarios. The first one is to use range-based localization with assistance from anchors. However, if the robot is near the bottom of the enclosed tank and it is occluded from beacons/anchors, it will not be able to localize accurately due to NLOS distance measurements. Various NLOS detection and mitigation techniques for cellular, Ultra WideBand (UWB) and sensor robot network localization have been proposed in the literature [1], [6], [15], [7], [17], [16]. However all these require that *the NLOS distances form the minority of the total available distance measurements*. The other option is to use SLAM-based approaches [3]. However, SLAM-based approaches have disadvantages including requirement of loop closure, expensive sensors and that measurements be corrupted by errors with known distributions. In such a scenario, we propose a solution *where the other robots in the cluttered environment are used to assist the concerned robot in localization*.



(a) Robot may detect an unusual event but clutter may render localization difficult.

(b) Neighbouring robots can be used to assist the concerned robot to localize with high accuracy.

Fig. 1. Motivation for using localizers for assisting in localization of robots in cluttered environments.

This paper proposes a new technique, namely Adaptive Placement for DV-Distance (APDV), whereby a group of special purpose nodes, called *localizers*, dynamically adapt their positions in the cluttered environment in order to assist an unlocalized node, referred to as *sensor* robot, to estimate its position. Fig. (1) shows an example of this solution. Fig. (1a) shows a robot, that may have detected an unusual environmental phenomena and needs to be localized accurately

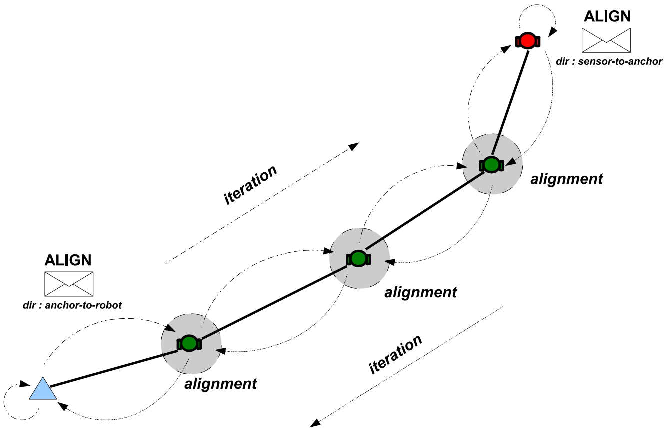


Fig. 3. Working of the APDV algorithm towards refining the distance measurements obtained via initially through the shortest-path-distance search of the DV-Distance algorithm.

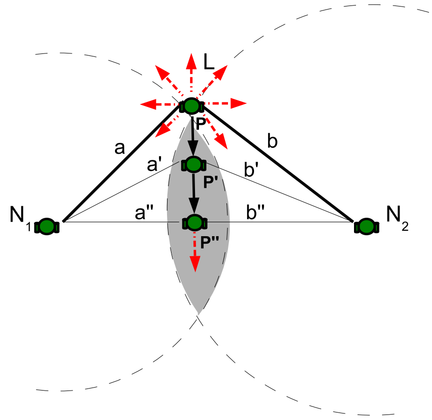


Fig. 4. Alignment procedure of L with neighbours N_1 and N_2. L chooses the direction (out of N_{dir}(=8) directions) which offers the maximum decrease in the sum of distances to its neighbours (a+b). The procedure completes when condition $(a' + b') < (a + b)$ no longer holds.

to report the location of the reading, is unable to localize due to the presence of clutter. Neighbouring robots can be used to assist it in this situation, as seen in Fig. (1b). Multi-hop localization, namely the DV-Distance algorithm, is used to actually localize the sensor. The key advantages of this approach are

1) It is completely distributed in nature and can be deployed in an ad-hoc manner.
2) It does not require the majority of distance measurements between the unlocalized sensor robot and anchors to be LOS in nature and works in situations where *all* distance measurements are NLOS in nature.
3) No prior information about the clutter topology is required.
4) The localizers themselves need not be localized, which prevents the accumulation of localization error commonly seen in multi-hop distributed localization techniques.

The remaining part of the paper is organized as follows: We describe our algorithm in detail in Section II, and evaluate it using simulated and real test-beds in Sections III and IV respectively. We discuss related work in Section V, and summarize our conclusions in Section VI.

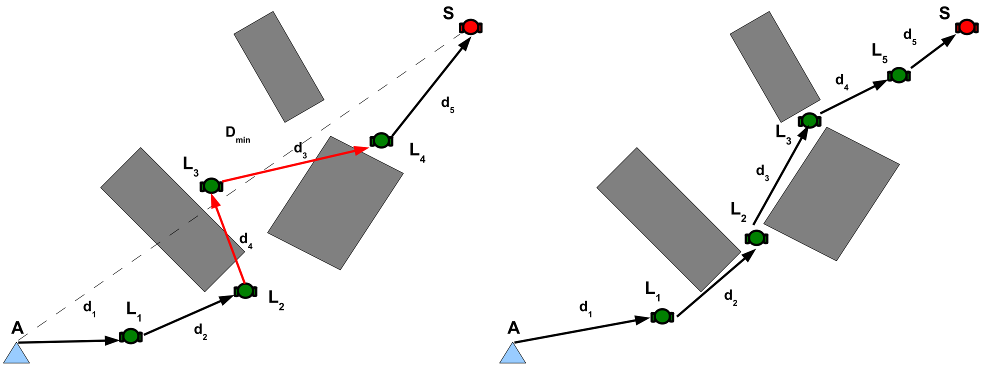
II. Proposed Algorithm

The aim of the proposed APDV algorithm is to minimize the cumulative multi-hop distances between a sensor robot and the available anchors. Fig. (2) shows an example with 3 localizers between a sensor robot S and an anchor A. In a clutter-free environment, the goal is to align the localizers in a straight line between the anchor and the sensor robot; in a cluttered environment, the goal is to move localizers so as to avoid NLOS distance measurements, which have large positive errors, and minimize the multi-hop distance between nodes A and S.

The APDV algorithm starts with a simple application of DV-Distance to identify the shortest chain of localizers between the sensor robot and the anchor. The algorithm then proceeds with an iterative application of the *alignment* process. The first iteration is triggered by the sensor robot, and results in a wave of localizer alignments from the sensor robot to the anchor. The second iteration is triggered by the anchor and moves in the opposite direction, and so on, as shown in Fig. (3).

Let us now discuss each iteration in detail. In the first one, sensor robot S sends an **ALIGN** message to its neighbor localizer. The localizer reacts by sending a **DIST-REQ** message to request distance measurements from its two neighbors. Its neighbors reply with **DIST-REP** messages that contain the requested distance measurements. The localizer then navigates to a carefully selected position to better align itself with respect to its neighbors. Once it moves to its new position, the localizer updates its distance to the anchor and broadcasts a DV-Distance advertisement with the new updated distance. It then passes the **ALIGN** message to the next localizer in the chain. Eventually the first localizer in the chain forwards the **ALIGN** message to the anchor itself. The anchor decides when to start a new iteration of the APDV algorithm based on whether *a single localizer was able to move to a new position*. In short, APDV repeatedly performs the alignment procedure in a series of iterations, and converges when none of the localizers in the chain moves to a new position. APDV is a fully distributed scheme that does not require knowledge of the clutter topology.

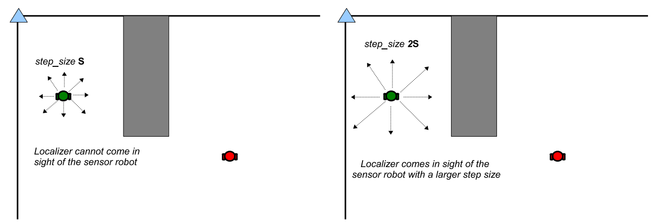
The key component of the APDV algorithm is the *alignment* procedure. When performing the alignment procedure, each localizer aims in align itself as much as possible. In other words, if we consider localizer L with neighbours N_1 and N_2 (localizers, anchors or sensor robot), such that the initial distances are a and b, the aim is to move L to a position such that the corresponding distances a' and b' is the least possible between the neighbours. It begins by L exhaustively evaluating all N_{dir} directions, around its current position P, for the one which yields the largest decrease in the sum of neighbour-



(a) Initial positions of localizers between the anchor and the sensor robot in a cluttered environment.

(b) Desired positions of localizers between the anchor and the sensor robot in a cluttered environment

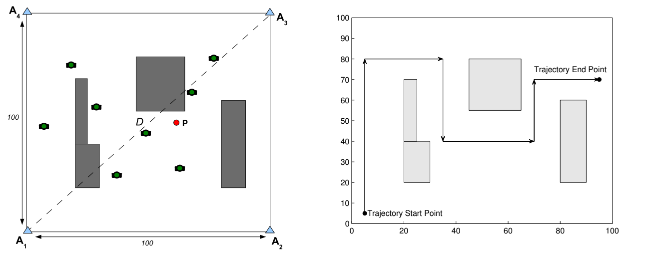
Fig. 2. APDV aims to align localizers between the sensor robot and the anchor node.



(a) Step Size = $\mathcal{S}$

(b) Step Size = $2\mathcal{S}$

Fig. 5. Step Size Threshold in APDV algorithm



(a) Clutter/node topology

(b) Trajectory of a sensor robot moving in a cluttered environment.

Fig. 6.

distances. If there exists such a direction Dir_c, L will move in that direction to the new position P'. L will then move a distance $\mathcal{S}$, again, in the direction Dir_c to position P'', takes fresh distance measurements to N_1 and N_2 and evaluates the position using the criteria given by $(a'' + b'') < (a' + b')$. L continues to do this until the sum of neighbour distances do not decrease, in which situation it moves back to the previous position and terminates the alignment procedure, as shown in Fig. (4).

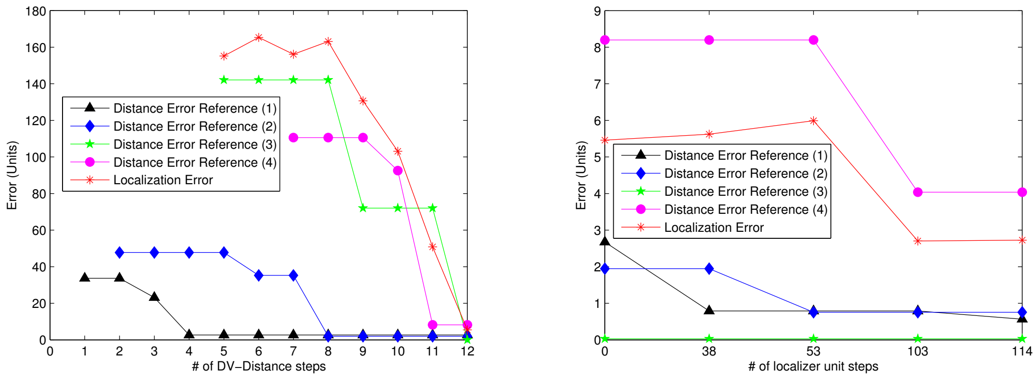
We have evaluated other variants of the alignment procedure where a localizer takes evaluates a random direction instead of exhaustively appraising all N_{dir} directions. However, we concluded that the above mentioned variant performs the best for clutter-prone scenarios. The termination proof of the APDV algorithm is omitted for lack of space.

The APDV algorithm is be adapted towards operating in cluttered environments by the use of the step size threshold. Here, instead of terminating the alignment procedure for the initial step size, $\mathcal{S}$, a localizer instead increases it and repeats the alignment procedure all over again. For example, in Fig. (5) we can see that the localizer will be able to to proceed to a better position with a step size of $2\mathcal{S}$ in the presence of clutter between the localizer and the sensor robot. If the alignment procedure converges again without moving to a new position, the step size is again incremented. These successive increments of the step size is bounded by the step size threshold, $\mathcal{S}_T$. When the localizer is not able to move to a fresh position (that offers more proximity to its neighbours) even when the step size is at the threshold, the localizer terminates the alignment procedure.

III. Simulation Experiments

In this section we evaluate the proposed algorithm in a simulation environment, and compare it with competing approaches. We use Prowler [12], a MATLAB-based discrete event simulator, for evaluating localization in clutter-prone environments. We have developed a 2D ray tracer for emulating NLOS distances between nodes obscured from each other due to clutter. The ray tracer returns the shortest indirect ray path that originates from a source and terminates at the destination node; indirect paths bounce off the clutter surfaces using Fresnel reflection.

Fig. (7) shows the performance of a combination of DV-Distance and APDV in progressively reducing the distance and consequently the localization errors. The sensor robot is placed at P and 8 localizers are scattered amongst the clutter as seen in Fig. (6a). The progress of DV-Distance over time while localizers remain fixed in their initial positions can been seen in Fig. Fig. (7a). DV-Distance gradually finds the shortest paths to all four anchors and yields a localization error of about six units. The APDV algorithm then takes over and, via moving localizers carefully among the clutter, reduces the localization error to less than three units, as can be seen in Fig. (7b).



(a) DV-Distance in progress.

(b) APDV in progress.

Fig. 7. The sensor robot is initially localized using DV-Distance. The localization error in the cluttered NLOS-prone environment is then further reduced using APDV.

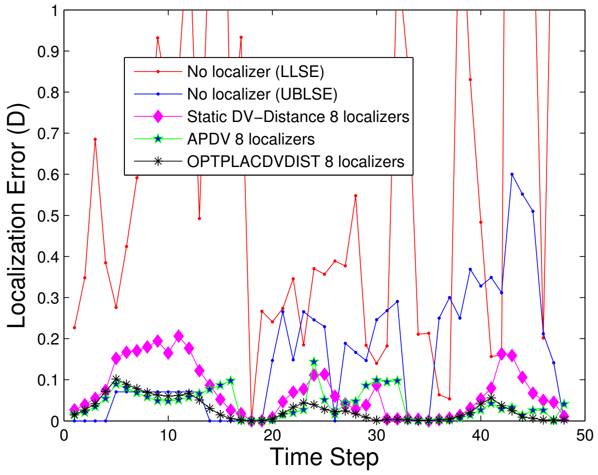


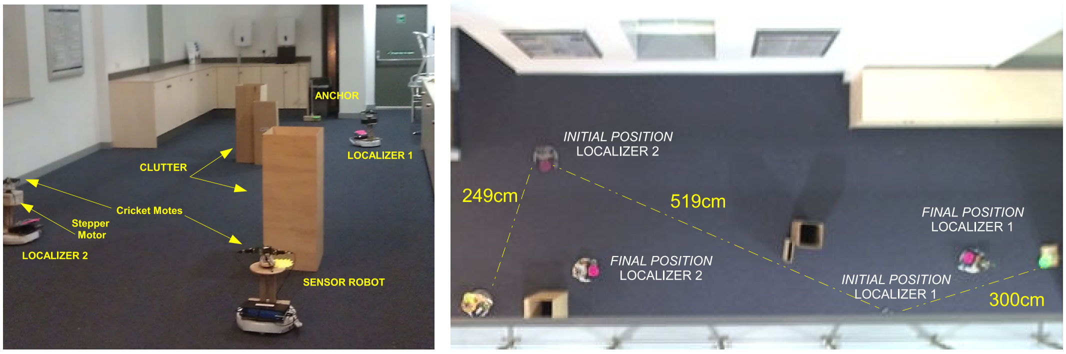
Fig. 8. Comparision of APDV with single-hop localization, Static DV-Distance and OPTPLACDVDIST

We compare the the performance of the proposed APDV algorithm with four competing approaches:

1) *No localizer (LLSE)* : Thius refers to single-hop localization that does not make use of localizers. It takes as input one-hop reflected NLOS paths from anchors to the sensor robot, and uses the linear least squares method for localization
2) *No localizer (UBLSE)*: This is similar to *No localizer (LLSE)* except that it uses an improved least squares estimator designed to tackle NLOS distances by taking into account upper-bound constraints [16]
3) *Static DV-Distance*: This is the existing DV-Distance algorithm, which makes use of localizers, but does not attempt to adjust their positions
4) *OPTPLACDVDIST*: This is an oracle algorithm proposed in [5], which assumes knowledge of the clutter topology and the sensor robot position, and finds localizer placements that minimize the anchor-to-sensor-robot multi-hop distances.

The initial localizer placement is as shown in Fig. (6a) and the mobile sensor robot follows the trajectory seen in Fig. (6b). Fig. (8) shows the results of comparing the above mentioned techniques. The x-axis shows time as the mobile sensor robot moves along its trajectory. The y-axis measures the localization error of the various techniques in terms of the longest diagonal of the cluttered area D (as seen in Fig. (6b)). Fig. (8) clearly shows that the *No localizers (LLSE)* approach is not practical in cluttered environments, since reflected NLOS distance measurements lead to enormous localization errors. *No localizers (UBLSE)*, however, performs very well during the early phase while degrading in performance later on. This is due to the fact that initially the sensor robot had only one NLOS distance (from anchor A_3), while later on the robot has at least two NLOS distances and thus LOS distances no longer form the majority of the available distances. The localization accuracy is significantly improved when fixed localizers are used in *Static DV-Distance*. However, this algorithm suffers when localizers do not happen to form tight multi-hop chains around the clutter, or use NLOS distance measurements among themselves. The proposed APDV algorithm, which carefully moves localizers to address the zig-zag and NLOS problems, outperforms Static DV-Distance by up to an order of magnitude. We point out that APDV is close in localization accuracy to *OPTPLACDVDIST*, which is an oracle algorithm providing a lower bound on anchor-to-sensor-robot distance errors. The proposed algorithm is thus a practical distributed algorithm that is empirically shown to achieve near optimal performance.

Next, we investigate the effect of the number of localizers available in the cluttered environment on the performance of the APDV algorithm. Fig. (9) shows the effect of varying the number of localizers, from 2 to upto 12, on the performance of APDV. As expected, the distance errors and the localization error both decrease as we introduce more localizers. The variance in the localization error along the entire sensor robot trajectory also decreases by increasing the number of localizers.



(a) Experimental setup for two localizer configuration. The localizers (with red markers) form a multi-hop distance chain between the sensor robot (yellow marker) and the anchor (in the far end of the picture).

(b) Experimental setup with 2 localizers, clutter topology 2, localizer step-size is 50cm. The actual distances are marked. The faded Create robot images represent the start positions.

Fig. 10. Experimental evaluation of APDV using the iRobot Create robotic platform and MIT-Cricket motes for distance measurements.

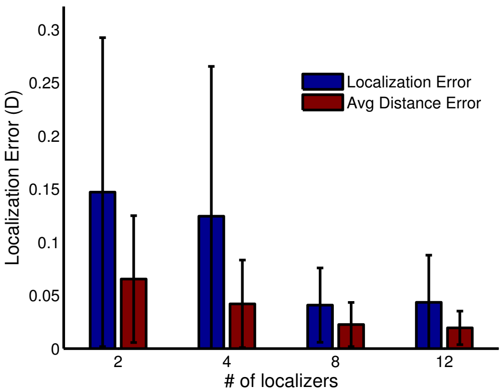


Fig. 9. Effect of the number of localizers on the performance of APDV

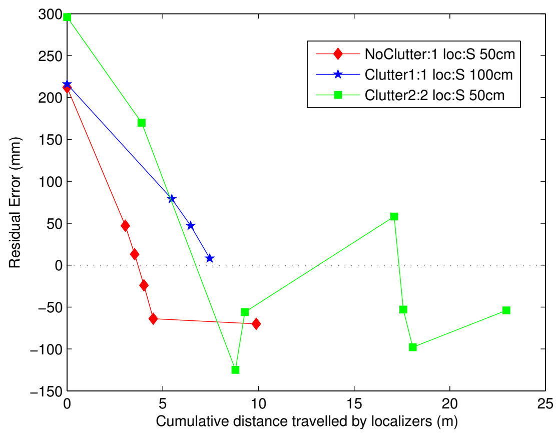


Fig. 11. Evaluation of APDV in real-world testbed experiments with Roomba Create robots and MIT Cricket distance measurement motes.

IV. Experiments with Real Hardware

In this section, we evaluate a proof-of-concept demonstration of the proposed APDV algorithm on a real test-bed for a single pair of anchor and sensor robot. We have built a mobile robotic platform using iRobot Create robots which are equipped with MIT Cricket distance measurement motes [10]. The Cricket motes have a maximum measurable range is around 12m when face-to-face but quickly decreases to 4-8m in the presence of obstacles, where the clutter topology and obstacle material play a vital role in determining the range. Since the ultrasound transducers on the Cricket motes are not omnidirectional, we use a formation of two Cricket motes, arranged back to back, that is rotated 360° for taking distance measurements. The APDV algorithm is implemented in Java and runs off the net-book mounted on the Creates. The original TinyOS code on the MIT Cricket motes has been modified to enable the transmission and reception of various messages used by the algorithm, in addition to the default distance measurement functionality of the MIT Cricket motes themselves.

The experiments were been conducted in the closed corner of our department atrium, as shown in Fig. (10a). The localizers are then used to reduce the error of the anchor-to-sensor-robot multihop distance. We use custom built plywood structures as obstacles as well as ground-level wooden blocks in the clutter free scenario. The communication range of the anchor does not reach the sensor robot even in line-of-sight conditions. We used step sizes, $\mathcal{S}$, of 50cm and 100cm and fixed $N_{dir} = 4$. We evaluated three settings: 1) With single localizer and no clutter; 2) With single localizer and clutter and 3) With two localizers and clutter (as seen in Fig. (10b)).

Fig. (11) shows the progressive reductions in the residual error (difference between multi-hop distance and true Euclidean distance) against the cumulative sum of distances traveled by the localizer(s). In case of the clutter-free scenario with 50cm step-size we find that the localizer makes a number of moves using the direction feedback, before halting near the Euclidean line joining the anchor and sensor robot. Due to distance measurement errors, we found that despite being close to the Euclidean line itself does not necessarily mean a lower distance error. In case of the two localizer setting, we find that the multi-hop distance is fluctuating about the true Euclidean distance, as opposed to strictly decreasing as in the single localizer cases. The reason for this is that whenever a localizer begins its alignment procedure, it performs an initial distance measurement to the previous node. The accuracy of that distance measurement impacts the distance error reduction in the subsequent alignment procedure as well as the subsequent residual error. Nevertheless, we find that APDV delivers a reduction in distance error of about 82% in case of two localizers and 96% in case of a single localizer.

V. Related Work

There exists a large body of work in the area of localization in cluttered NLOS-prone environments. These can be subdivided into NLOS-detection techniques and NLOS-mitigation techniques. Venkatesh et al. [15], among others, introduce a technique that aims to detect and eliminate individual NLOS distance measurements from the all available distance measurements. On the other hand, Chen et al. [1], Wang et al. [17], Kung et al. [7] and Jourdan et al. [6] propose NLOS-mitigation techniques seek to use all distance measurements, both LOS and NLOS, to calculate the position. Both categories require that that the number of LOS distances are greater than the NLOS ones in order to perform well.

Multi-hop localization in concave environments where the error in the distance measurements is primarily effected by the overestimating nature of multi-hop distances (dependant on network connectivity and topology) than from the actual incidence of NLOS distance measurements has extensive research [16], [11], [7], [17]. Wang et al. [16] proposes an improved least squares position estimation technique for handling overestimated distances using distance upper-bounds. The authors, however, assume that the distance measurements between nodes will be fairly accurate themselves, i.e., they will be LOS in nature.

Node mobility has been employed in previous literature to improve the quality of localization in multi-hop localization techniques [13], [14]. The MLM approach [14] uses a combination of a modified Biased Kalman Filter (MBKF) and shortest path distance (SPD) to estimate distance measurements whose error is less than direct NLOS distances from the anchors. The mobile nodes estimate distances to anchors and initially calculate their positions using multidimensional scaling (MDS) and thereafter using iterative localization to further refine the position estimates. However, iterative localization requires a large number of nodes for successful localizations than, for instance, DV-Distance [18], [5]. Moreover, the paper does not address the scenario where a mobile node would want to localize at a particular location of interest.

VI. Future Work and Conclusion

In this paper, we proposed the APDV algorithm which uses intermediate nodes, referred to as localizers, together with DV-Distance algorithm to estimate sensor-robot-to-anchor distances in cluttered NLOS-prone environments. APDV carefully places localizers among the clutter in order to improve localization accuracy requiring localizers to communicate with only their neighbours and without prior knowledge of the clutter topology. We have performed an extensive evaluation of the algorithm in simulated and real network settings, and have shown that it can improve localization accuracy by an order of magnitude compared to competing approaches. For future work, we would like to study the impact of clutter on the localization error in the OPTPLACDVDIST and the APDV algorithms. We would also like to look into various localizer coordination schemes in the APDV algorithm that can improve the completion time of the algorithm.

VII. Acknowledgements

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