Scalability Issues in Localizing Things

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***Abstract*—Localization will play an important role in the Internet of Things (IoT), and will employ several complementary mechanisms, each applicable to Things with different characteristics. This paper investigates the impact of scale and mobility on wireless multi-hop localization mechanisms, which specifically target Things with limited capabilities inhibiting them for self-localization, i.e., cannot locally perform trilateration or angle of arrival analysis. Building on a representative system for wireless multi-hop localization, we evaluate the impact of network size and node mobility on various operational aspects, including number of messages sent, collisions, localization accuracy, in addition to the percentage of unlocalized nodes. We also show how a basic optimization can result in substantial gains. More critically, however, we establish the need for further optimizations in realizing localizations in IoT.**

I. Introduction

The Internet of Things (IoT) emphasizes a paradigm shift in the next generation internet that allows for the connectivity of multitude of users and devices. The essential concept is to connect variety of communicating Things with each other through a unique addressing scheme using the Internet [1]. A Thing can be either a physical object (e.g. chair, fridge or lamp), a digital object (e.g. software, songs or movies) or a living object (e.g. plants, animals or humans) [2]–[4]. In the near future IoT will create huge dynamic networks with trillions of individually identifiable objects, with estimates expecting 50 billion devices to be connected by 2020 [5].

A central functionality in the IoT is the localization of Things, which aims to identify physical positions of Things [2], [6]. In realizing the IoT, there are definite challenges that need to be addressed in order to provide prompt and reliable localization. One of the main challenges in IoT is the heterogeneity of devices. Devices in IoT vary in terms of processing, memory size, mobility, and communication characteristics. Some devices are able to autonomously infer their position on their own, using either satellite (GPS) or terrestrial mechanisms to gain this awareness. A position of a certain network element can also be computed through location knowledge of other elements in the network. This "anchoring" can sometimes be performed using distance and bearing measurements like signal strength and time of arrival. Anchoring can also inferred from network information. Meanwhile, less capable devices with limited functionality will not be able to autonomously identify their own positions using GPS. Note that this limitation can sometimes be temporal, where a GPS enabled device is beyond the line-of-sight coverage. In such instances, mechanisms such as relative positioning and wireless multi-hop localization become crucial [2], [7]. Such localization modes are the focus of this work.

The objective of this work is to investigate the impact of scale on wireless multi-hop localization mechanisms, and to understand their general applicability to other localization modes. Our interest spans the aspects of both network requirements and localization accuracy. Great dependence in the IoT will be on wireless connectivity. Moreover, and given the sheer number of Things involved, in addition to projected variance in their position/mobility profiles, it becomes crucial to understand how current systems can cope with both scale and mobility. Equally crucial is satisfying the requirements of promptness and accuracy in the localization procedures.

To achieve this objective, we perform "stress-testing" on a representative system for wireless multi-hop localization technique selected for its operational efficiency and accuracy [8]. The system depends on fixed anchor nodes that are aware of their location and sensor network responding and processing localization information send by the anchors, and is implemented with slight modifications to enhance localization accuracy. The testing involved increasing the size of the sensor network, in addition to increasing node mobility. Operational aspects such as the number of messages generated, received and dropped; number of collisions, localization accuracy and percentage of unlocalized nodes were measured. Results invariably indicate definite scalability issues at the different layers of operation. Moreover, while we illustrate that substantial gains can be achieved using a basic operational optimization, we also establish a maintained need for more innovative solutions.

The remainder of this paper is organized as follows. Section II positions and motivates this work. Section III provides the evaluation environment, giving an overview of the representative system for wireless multi-hop localization, elaborating on the implemented modifications and describing the suggested enhancement. Section IV discusses the results. Finally, Section V concludes and alludes to possible future directions.

II. Motivation and Related work

The intent of this section is to provide an overview of the different localization mechanisms used in the literature. We focus on techniques used in wireless sensor networks as they are more relevant to be used in IoT. In general, localization techniques focus on identifying the location or position of a sensor accurately, which can generally be classified into

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four main categories, depending on the type of measurements used for localization [9]–[11]. These categories are: Angle of Arrival, Received Signal Strength Indicator, Time of Arrival and Multi-hop measurements. Accordingly, relevant localization techniques are discussed in the following subsections.

A. Angle of Arrival (AoA)

AoA is used to define the propagation direction of the received wave based on some reference direction, known as orientation. AoA requires several ultrasound receivers or a multi-antenna array in order to estimate the position of a node. Niculescu and Nath proposed localization algorithm using AoA [12]. In their algorithm each node gets its position to neighboring nodes with respect to its own axis using the AoA. They tested their algorithm on static topologies only. Nasipuri and Li used a technique that can determine the position of sensor nodes by obtaining angular bearings relative to a set of fixed beacon nodes [13]. Each beacon node send periodically a unique RF signal in a narrow direction. The RF signal sent by the beacon node rotate at constant angular speed. the sensor node estimate its position based on the RF signal. Each sensor node needs at least three beacon nodes with additional beacon nodes for resolving errors results from multipath reflections (a total of four beacon nodes). In [14], Biswas et a. extend the semidefinite programming relaxation to localize nodes using angle information with or without the distance information.

The main drawback of these techniques in terrestrial systems is the possibility of error in estimating the directions caused by multipath reflections. Also, the evaluation of AoA becomes more cumbersome for mobile nodes, even at pedestrian mobility levels.

B. Received Signal Strength Indicator (RSSI)

RSSI uses the information of transmitter power, power of received signal, and path propagation model to estimate the distance of the receiver from the transmitter. A node needs three or more beacon signal to compute and estimate its location. Lim et al. obtain a mapping between RSSI measurements and the effects of RF multi-path fading, temperature and humidity. After that, they use truncated Singular Value Decomposition (SVD) technique to map between the RSSI measurements and the actual geographical distance variations. The system is designed for indoor space [15]. A probabilistic model of RSSI range measurements is proposed by Peng and Sichitiu to address the problem of uncertainties and irregularities in radio communication patterns [16]. They use the log-normal model, which assumes that a particular RSSI value can be mapped to a log-normal distribution of the distance between the two nodes.

Major drawbacks of RSSI method are summarized in multipath reflections, non line-of-sight conditions, and other shadowing effects that will lead to incorrect location estimates [13]. A combination of RSSI and other measurements are used to increase the accuracy of location estimates, as proposed in [17]–[19]. However, the nonuniform propagation model in outdoor environment makes RSSI methods unreliable and inaccurate localization technique for IoT.

C. Time-of-arrival (ToA) and time-difference-of-arrival (TDoA)

ToA and TDoA techniques uses the propagation time of a signal to estimate the distance for wireless node using a set of anchor nodes. The signal used for localization could be Radio Frequency (RF) or ultrasound. Savvides et al. send radio signals and ultrasound pulses continuously and estimate the distance between the sender and the receiver by multiplying the time difference of arrivals by the speed of the ultrasound. Another ranging technique relies on capturing the signal's time of flight. Youssef et al. [20] obtain the distance by multiplying time of flight by the speed of the signal.

In reference [21], authors find that when using ToA or TDoA in dense network as in sensor networks will cause large errors in estimating the distance. This is caused by the high propagation speed of RF signals, in which any small measurement error will cause a large error in the distance estimate. A solution for this problem is the use of ultrasound signals, which have low propagation speed compared to RF singles. However, this requires additional hardware in order to receive the ultrasound signals. This means it is hard to ably this to IoT domain, as we need to minimize the cost of nodes as much as possible. Also, these techniques will not be applicable to be used while nodes are moving around the network.

D. Multi-hop

Multi-hop localization techniques are based on connectivity and distance measures. In connectivity-based the sensor nodes use the position of anchor nodes to estimate their locations. Niculescu and Nath [22] proposed APS (Ad-hoc positioning system) algorithm that uses hop by hop propagation with the position of a well know landmarks nodes to calculate the distance between each node and the landmarks node. Then the system uses the distance between nodes and all landmark nodes as an input to the triangulation procedure that is used in the GPS algorithm. The algorithm only work for isotropic networks with limited mobility. Another work done by Savarese et al. [17] proposed AHLoS (Ad-Hoc Localization System) algorithm, where a small fraction of nodes have the knowledge of their position to know the position of other nodes using Atomic multi-lateration, collaborative multi-lateration and iterative multi-lateration algorithm. In AHLoS at least 3 nodes know their position in order to estimate the position of other nodes. Nagpal et al. [23] calculate a global coordination system in the network by estimating the Euclidian distance of a hop. The estimation algorithm uses the number of communication hops of the sensor nodes. When a node receives at least 3 gradient values (hop count), the node calculate the distance from the seeds and estimate its position based on the position of the seed.

Akbas et al. [8] localize the position of sensor nodes flooding in the Amazon River based on a stationary actors node placed at the blank of the river. Their localization algorithm uses multi-hop count between sensor nodes and actor node. Each sensor node keeps a single weight value for each actor it is associated with. This weight represents the minimum number of hops to reach actors. The actor node uses the weight to estimate the sensor node positions.

This category is the most suitable localization techniques for IoT domain as it can localize object 2 or 3 hop away from anchor nodes, which is the case in IoT environment. Moreover it can be used to localize moving nodes.

III. Evaluation Environment

Our evaluation environment relies on the wireless multi-hop localization system proposed by Akbas et al in [8]. This choice was motivated by the general applicability of wireless multi-hop localization to both multi-hop and single hop localizations. It was also motivated by the projected nature of how Things communicate in the IoT. More importantly, our own validations indicate that the system possesses a relatively higher operational efficiency, in addition to a robustness in localizing nodes at different mobility speeds.

In what follows, we provide an overview of the evaluation environment. In doing so, we also describe certain modifications that were made to system operation, in addition to an operational enhancement that — as will be illustrated in the following section — results in substantial performance gains.

A. Multi-hop Localization Algorithm

The system relies on both anchor nodes and a sensor network. Each anchor node periodically sends what is called weight update message to all its neighboring nodes that contains the anchor node's address (anchor ID) and the value of its own weight parameter k. During initialization the value of k is the same for all anchor nodes.

When a node receive a weight update message, it will first decrease the weight value by 1. If the weight value reaches zero, the node drops the packet, otherwise the node forwards the packet to the surrounding nodes. Each sensor node save the highest received weight for each anchor node in its weight table. Figure 1 shows an example for the weight table. The sensor node could save multiple weight for different anchor nodes, but it should save a single weight for each anchor node. The weight saved at the sensor node indicates how many hops this sensor node is away from the anchor node it saves a weight. In operation, a sensor node differs from an anchor node in that the sensor node will forward the weight update message if the weight did not reach zero, while the anchor node will drop the packet after it saves the weight value in the weight table.

After the sensor nodes build their weight tables as shown in Figure 1), they will forward their weight table periodically to the anchor nodes. The aim in sending the weight table is to enable the anchor node to calculate the estimated distance between an anchor node and all the senor nodes afflicted with the anchor node. The time to live for the packet is set with the maximum weight value saved in the table.

As the sensor nodes move around the network, the weight values saved at sensor nodes will not represent the number of hops between sensor and anchor node. This means the sensor node has to update their weight table periodically. In order to do so, the node saves the time it received the weight update packet. After that the sensor node subtracts the save time with the current time while sending the weight table packet. If the subtracted time exceeds a given threshold, the sensor node decreases the weight value by 1 until it reaches zero.

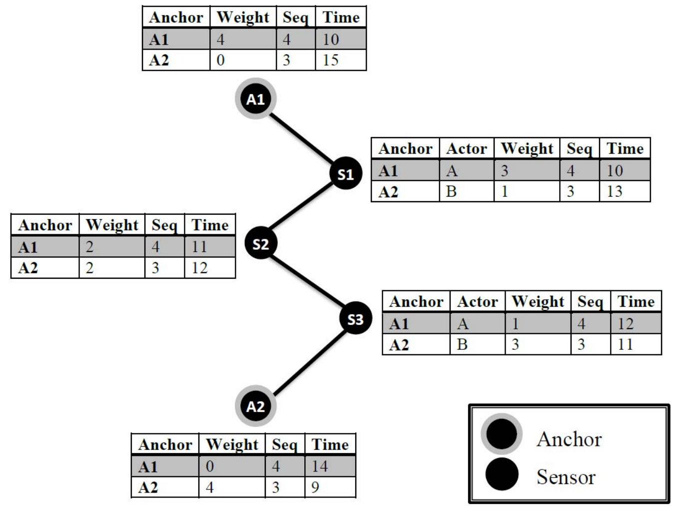


Fig. 1. Example for the weight tables built for each node.

When a sensor node receives a weight table packet it simply forwards that table to the surrounding nodes. Meanwhile, when an anchor receives a weight table packet, it starts to process the packet to calculate the estimated distance between itself and all the sensor node sent the weight table packet using the following equation:

$$d_{a,s} = w_{a,s} * h_a \tag{1}$$

where $d_{a,s}$ represents the estimated distance between anchor node A and sensor node S, $w_{a,s}$ is the weight of sensor node S for anchor node A and h_a is the average 1-hop distance of anchor A. After calculating the estimated distance for all the sensor nodes affiliated with the actor node, the anchor node forwards these values to the sink node.

Upon investigation, however, we observed that the accuracy of this equation can be improved by subtracting the weight of anchor node from $w_{a,s}$, as follows:

$$d_{a,s} = (k_a - w_{a,s}) * h_a \tag{2}$$

where k_a is the weight of anchor node A. Our implementation utilizes this modification.

The sink node uses all the received estimated distance "$d_{a,s}$" for every sensor node calculated by actor nodes. For a given sensor node, if at least three estimated distance are calculated for different anchor nodes, then the position of this sensor node can be estimated using the multi-lateration. The estimated position can be represented using the following system of equation in the matrix form:

$$\begin{bmatrix} 2(x_n - x_1) & 2(y_n - y_1) \\ 2(x_n - x_2) & 2(y_n - y_2) \\ \vdots & \vdots \\ 2(x_n - x_{n-1}) & 2(y_n - y_{n-1}) \end{bmatrix} \begin{bmatrix} x_s \\ y_s \end{bmatrix} =$$

$$\begin{bmatrix} (d_1^2 - d_n^2) - (x_1^2 - x_n^2) - (y_1^2 - y_n^2) \\ (d_2^2 - d_n^2) - (x_2^2 - x_n^2) - (y_2^2 - y_n^2) \\ \vdots \\ (d_{n-1}^2 - d_n^2) - (x_{n-1}^2 - x_n^2) - (y_{n-1} - y_n^2) \end{bmatrix} \tag{3}$$

where (x_i, y_i) $\forall i = 1$ to n, represent the actual position for n actor nodes, $d_i \forall i = 1$ to n, represent the estimated distance between these actor node and the sensor node, and (x_s, y_s) represents the estimated position for a sensor node. The above matrix can be represented in the following form for simplicity $Ax - B$, where A represents the left hand side, B represents the right hand side and x represents the estimated position for a sensor node. To solve this equation least square error is used which result in the following equation [1]:

$$x = (A^T A)^{-1} A^T B \tag{4}$$

There is a chance that $(A^T A)^{-1}$ results in a singular matrix, which does not have an inverse. A solution for this problem is to solve the overdetermined equation 3 using multiple simultaneous equation only if $(A^T A)$ returns a singular matrix. To explain how we used multiple simultaneous equation to solve equation 3 assume we have 5 actor node estimated the distance for a sensor node. Therefore, we have 4 equations in 2 variables. We get the solution using the first 2 equation, then we get the solution using the second and third equation and so on. This will result in having 6 results for x and y. To get a final solution, we get the average for these 6 results.

We validate the results of the algorithm. And the algorithm gives less error distribution after the minor modifications we made in equation 2 and equation 4.

B. Aggregated Multi-hop Localization

In Akbas et al. [8], when a sensor node receive either a weight update packet or weight table packet, the sensor node will forward this packet to the surrounding nodes at once. This behavior (receive then forward) generates huge traffic from sensor nodes that affects the performance for the transmission. This could be acceptable in the WSN environment, but it affect the performance of the communication in IoT environment. The reason for the huge traffic traffic generated is that the packet is broadcasted to all neighbor nodes. This means it is important to reduce the number of messages generated while implementing localization algorithm. We observe the same problem “A huge traffic is generated during the localization process” for the other localization algorithm

To solve this problem, we propose that sensor nodes only transmit weight update packets or weight table packet in a predefined time. This means when a sensor node receives a packet it will store it and build an aggregated message. When the timer for the transmitter expires the sensor node forward the two aggregated messages, the first is for the *weight update packet*, while second is for the *weight table packet*. After applying this behavior (receive, save then forward) will dramatically reduce the number of message send.

[1]This form differs from the one used in [8], which errs in evaluating x using $x = A^T (AA^T)^{-1} B$.

IV. Simulation setup and Results

In this section we review results obtained through our evaluation environment. We extended the ns-2 network simulator [24] to support wireless multi-hop localization for wireless node, and utilized BonnMotion to generate various mobility traces based on the Random Waypoint mobility model [25]. In the setup, nodes are uniformly distributed in a simulated area of 100x100 unit blocks. The choice of area was made to ensure the full connectivity of the wireless sensor networks when even the least number of nodes is distributed, which is 25 nodes. In the following evaluations, an anchor node sends weight update packet every 10 seconds. The transmission range for sensor nodes is set to 40 meters, and the anchors and sink nodes are connected through a high-speed backbone network. Twenty five (25) anchor nodes in addition to 1 sink node are used. Simulations are made to run for a period of 100 seconds. Impact of scale is evaluated through varying size of the sensor network from 25 nodes to 200 in increments of 25 nodes. The effect of mobility is verified through varying mobility speeds based on the Random Waypoint model, and detailed below in the relevant experiments. The performance metrics are averaged over ten different topology runs generated using distinct random seeds.

In our evaluations, we investigate several aspects of operations. We describe below our findings given performance metrics that best illustrate the impact of scale and mobility on wireless localization algorithms. The metrics are defined as follows:

- **Total number of packets sent** Comprises the total number of packets transmitted for two types of messages. The first type includes weight update messages, which are generated by anchor nodes and forwarded by the sensor nodes. The second includes the weight table messages, which are generated and forwarded by sensor nodes.
- **Total number of packets received.** The total number of packets received at anchor and sensor nodes.
- **Total number of packets dropped** Comprises the message dropped due to redundancy, i.e. a weight update or weight table message that have already been received.
- **Total number of packet collisions** Reports the number of packet collisions at the MAC layer.
- **Mean error in Euclidean distance** Reports the mean error in computing the Euclidean distance between estimated position and actual position for each sensor node.
- **Percentage of unlocalized nodes** Localizing any sensor nodes requires at least three reports. This metric report the percentage of the nodes for which at least three distance reports were not received.

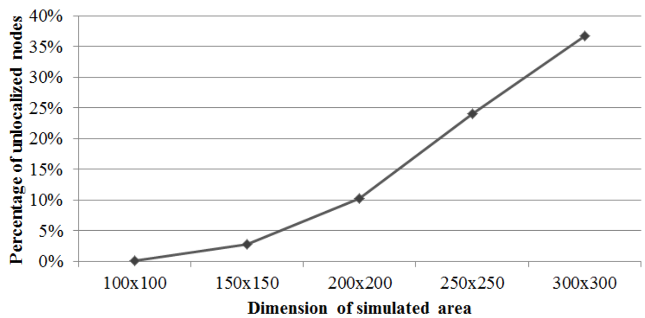


Fig. 2. Percentage of unlocalized nodes in a given simulation area.

In addition to investigating the effect of scale and speed on multi-hop localization, we also investigate the possible improvements provided by the simple aggregation discussed in Section III. Consequently, the figures discussed below show the localization results for both with and without the suggested aggregation.

A. Elaboration on the Selection of the Simulation Area.

This section elaborates on the selection of a 100X100 for the following sequence of results. To ensure neutrality, we seek an area that would eliminate the effect of connectivity on the results. An area that ensures fully connectivity when the least number of nodes is distributed, 25 nodes in our case, would consequently ensure connectivity for a higher number of nodes.

In order to investigate the effect of simulated area on node connectivity, a scenario is used where only 25 anchor nodes and 25 sensor nodes are simulated. The 25 sensor nodes represent the Things that need to be localized. The weight parameter, k, is set to 4 to allow Things to connect to anchors node using 4 hops. Figure 2 shows the simulated area represented relative to the percentage of nodes that failed to be localized. Confirming intuition, as the simulation area increase the percentage of nodes that are not localized also increases. A 100x100 simulation area, however, satisfies our connectivity objectives.

B. Impact of Network Size

In order to investigate the effect of scalability on localization, the number of node is increased from 25 to 200 by increasing 25 nodes each time. The weight parameter, k, is set to 4 to allow Things to connect to anchors node using 4 hops. The impact of network size is evaluated both in a static (no mobility) scenario and a mobile scenario. In the latter, a node's speed ranges between 4.5 km/h and 5.5 km/h, which are nominal pedestrian speeds. The results for the static and mobile scenarios are respectively shown in Figure 3 and Figure 4. In each, the sub-figures illustrate the impact on the total numbers of (a) packets sent; (b) packets received; (c) packets dropped; and (d) packet collisions.

The value of the different metrics consistently increases as the number of nodes is increased. This is observed in both static and mobile settings. When aggregation is not employed, despite the redundancy check, a great number of packets are generated. For example, at 125 nodes, 150,000 packets are either sent or forwarded in the static setting as shown in Figure 3(a), while almost 2,000,000 packets are received as shown in Figure 3(b). A similar trend can also be observed in the mobile setting (100,000 to 800,000 at 125 nodes). Note that this great discrepancy is due to the broadcast nature of the wireless medium, i.e., all receivers in the vicinity of a sender or forwarder node receive the broadcasted message. This very nature also justifies the numbers for packets dropped and collisions as shown in Figures 3(c) and 3(d). Lesser numbers are also experienced in the mobile setting as nodes move beyond each other's vicinity more frequently.

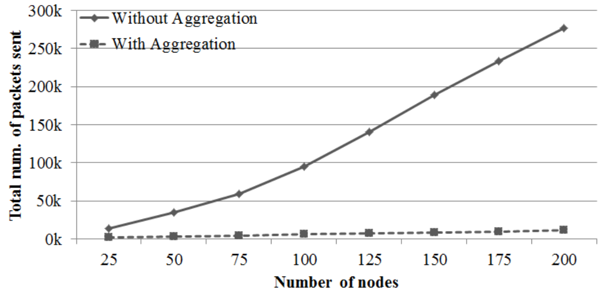
The impact of the suggested optimization is apparent in both Figure 3 and Figure 4. Recall that the optimization simply involves the use of a hold time prior to forwarding received messages and tables while aggregating them in one transmission. In the static setting, this modification reduces the number of sent and forwarded messages from almost 300,000 to less than 20,000 at 200 nodes as shown in Figure 3(a), and relatively diminishes the number of collisions experienced in the network as shown in Figure 3(d). Similar trends can also be observed in the mobile setting as shown in Figure 4.

C. Impact of Mobility

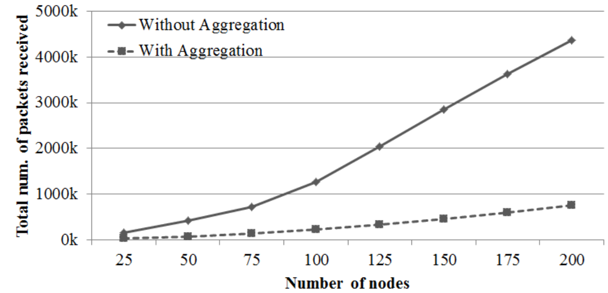
The experiments discussed in the previous subsection were concerned with isolating the impact of network size. Here, we isolate the impact of mobility on localization, and continue to identify the effect of the suggested optimization. In the scenario employed, mobility speed ranges between 1 m/s to 9 m/s (= 32 km/h). In Figure 5, we show two set of results, one for 25 nodes and the other for 200 nodes. Figures 5(a), 5(c), 5(e) respectively show the total collisions, mean error in Euclidean distance and percentage of computable nodes for 25 nodes; Figures 5(b), 5(d), 5(f) show the same for 200 nodes.

In terms of collisions, the figure confirms trends that were discussed above. Here, however, we note a general reduction in the number of collisions as the mobility increases. As noted above, this decrease is justified by the variations network's topology rather the operational qualities of localization. Node mobility reduces the possibility of receiving a message, in turn reducing the load of message sending and forwarding on the medium and, hence, the number of possible collisions. It is more critical, however, to observe the impact of aggregation on collisions, which can be justified by substantial reduction in sending and forwarding load as a result of aggregation.

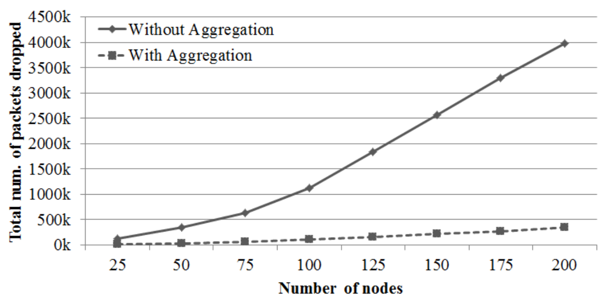
The remaining sub-figures illustrate further operational advantages of suggested aggregation. The localization employed relies on an over determined computation, whereby localization accuracy improves as more messages are received per a localized node. This increase in accuracy is apparent in Figure 5(d), and is sustained as node mobility is increased. Meanwhile, while Figures 5(e) and 5(f) illustrate the impact of mobility on the percentage of unlocalized nodes, they also show the impact of aggregation in reducing this percentage - especially at higher node mobility.



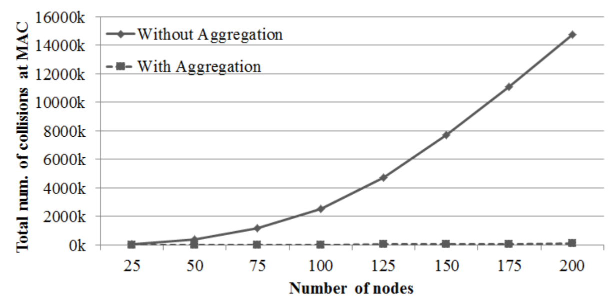
(a) Total number of packets sent



(b) Total number of packets received

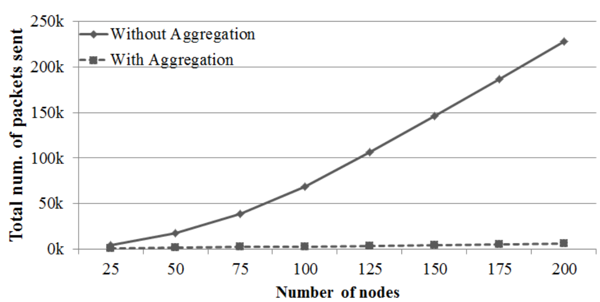


(c) Total number of packets dropped

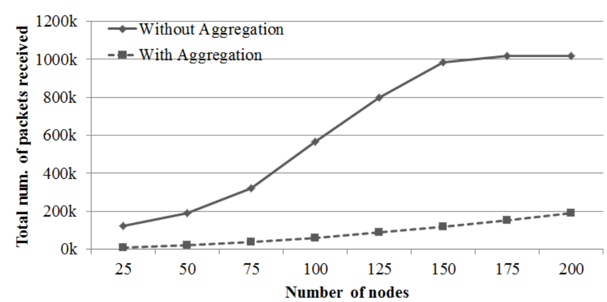


(d) Total of collisions at MAC layer

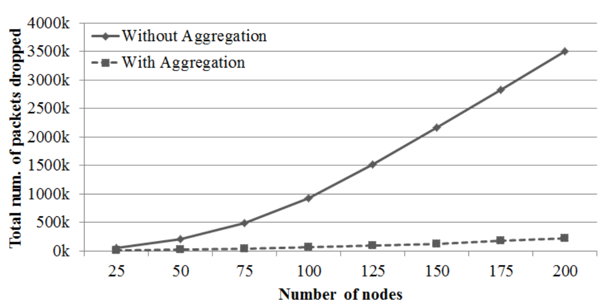
Fig. 3. The effect of increasing the number of nodes on the evaluation metrics - static setting with weight k = 4.



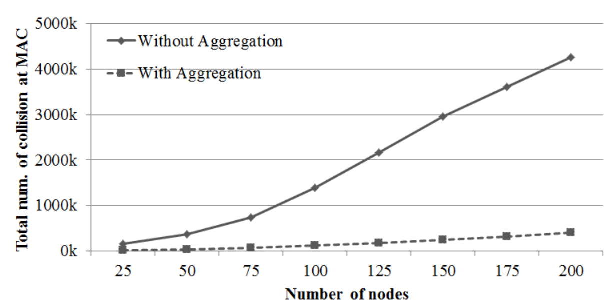
(a) Total number of packets sent



(b) Total number of packets received

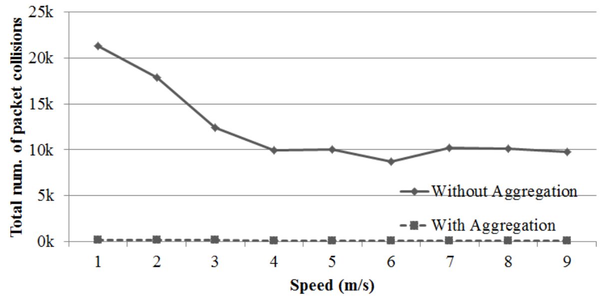


(c) Total number of packets dropped

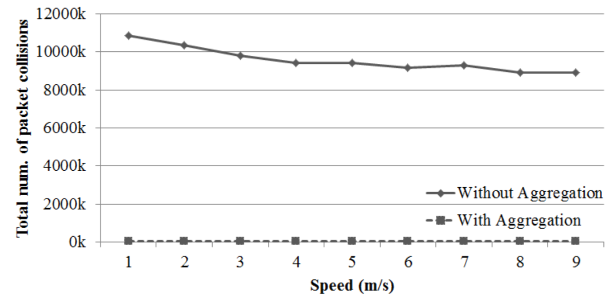


(d) Total number of collisions at MAC layer

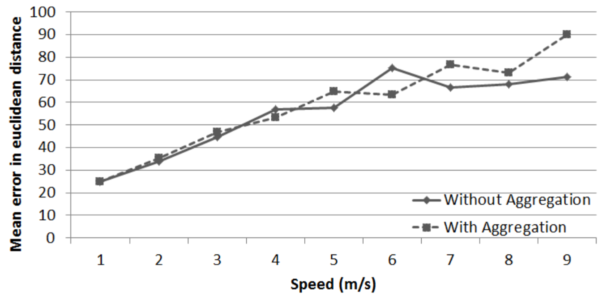
Fig. 4. The effect of increasing the number of nodes on the evaluation metrics - mobile setting (4.5 5.5 Km/hr) with weight k =4



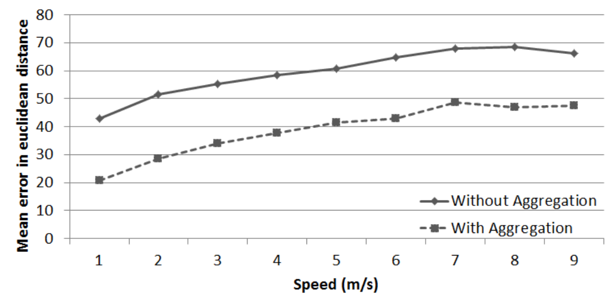
(a) Total number of collisions at the MAC layer (25 nodes)



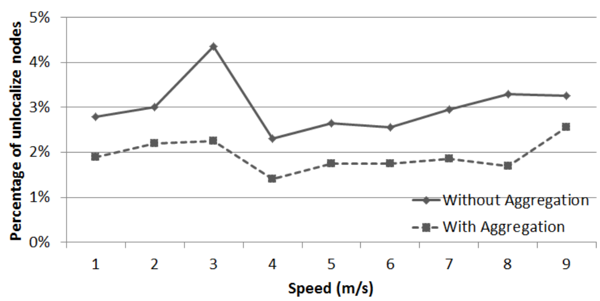
(b) Total number of collisions at the MAC layer (200 nodes)



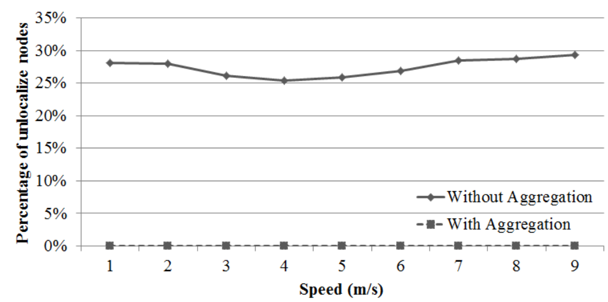
(c) Mean error in computing Euclidean distance (25 nodes)



(d) Mean error in computing Euclidean distance (200 nodes)



(e) Percentage of unlocalized nodes (25 nodes)



(f) Percentage of unlocalized nodes (25 nodes)

Fig. 5. Metrics calculated using different speed.

D. Discussion and Further Observation

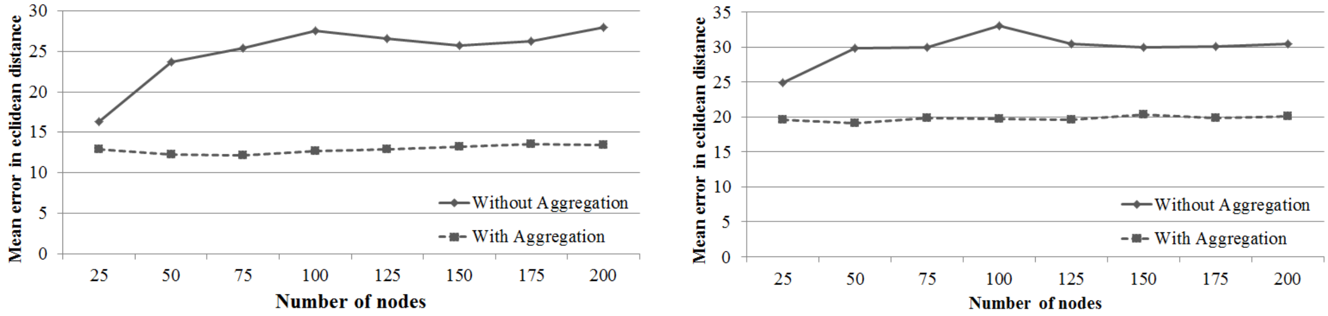
In addition to other extensive evaluations, the above results indicate a need for carefully designed localization algorithms. Even for the suggested aggregation algorithm, further optimization remain possible. For example, the exact relationship between hold time and mobility need to be further explored. Another issue of concern is that of MAC operation, especially when it comes to functionalities such as localization. This impact of MAC is apparent in Figures 3(d) and 4(d) which show the number of collisions in MAC layer, which even after aggregation is quite substantial.

It is also important in optimizing or re-designing the localization procedures to mind the ultimate objective, which is accurate localization. In investigating the suggested aggregation, we explored its impact on localization accuracy, or rather error. Figure 6 shows the mean localization error for the static and mobile settings discussed in Section IV-B above. In the figure, it can be observed that aggregation reduces the localization error. This decrease in error results specifically from aggregation connecting the sensor nodes to more anchors.

Enhancements to localization procedure are hence required to be made at several layers, especially when it comes to accommodating scale and mobility. In this study, we initially isolated the localization functionality from other network operations. We understand, however, that more elaborate studies can identify further optimizations, where enhancements such as message sharing between different functionalities can be explored. Such expansive view is indeed the subject of our future investigations.

V. Conclusion

The intent of this work was to investigate the impact of scale and mobility on wireless multi-hop localization. Such localization mechanisms complement other mechanisms, and is specifically useful in localizing elements that cannot be self-localized due to limited capabilities. Collectively, however,



(a) Static setting

(b) Mobile setting

Fig. 6. Mean error in computing Euclidean distance with weight k =4.

localization mechanisms play a crucial role in the Internet of Things (IoT), where location-based services and functionalities will be important for both the network and the users. With expectations that 50 billion devices will be connected by 2020, it becomes more important to simultaneously reduce the network requirements and enhance the accuracy of localization procedures. Our investigations examined various operation aspects, including number of packets transmitted and received, network collisions, localization accuracy and percentage of unlocalized nodes. The results indicate that a serious need exists for optimization. We also investigated the effect of a basic optimization, which resulted in substantial enhancement in both network operation and accuracy.

While we also investigated effect of a basic optimization, which resulted in substantial enhancement in both network operation and accuracy, a great need for improvement persists. Our specific intent is to identify possible enhancements by exploring cross-layer design and message sharing between different network functionalities.

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