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Low communication cost (LCC) scheme for localizing mobile wireless sensor networks

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Abstract In recent years, the number of applications utilizing mobile wireless sensor networks (WSNs) has increased, with the intent of localization for the purposes of monitoring and obtaining data from hazardous areas. Location of the event is very critical in WSN, as sensing data is almost meaningless without the location information. In this paper, two Monte Carlo based localization schemes termed MCL and MSL* are studied. MCL obtains its location through anchor nodes whereas MSL* uses both anchor nodes and normal nodes. The use of normal nodes would increase accuracy and reduce dependency on anchor nodes, but increases communication costs. For this reason, we introduce a new approach called low communication cost schemes to reduce communication cost. Unlike MSL* which chooses all normal nodes found in the neighbor, the proposed scheme uses set theory to only select intersected nodes. To evaluate our method, we simulate in our proposed scheme the use of the same MSL* settings and simulators. From the simulation, we find out that our proposed scheme is able to reduce communication cost—the number of messages sent—by a minimum of 0.02 and a maximum of 0.30 with an average of 0.18, for varying node densities from 6 to 20, while nonetheless able to retain similar MSL* accuracy rates.

Keywords Adjacency matrix · Communication cost · Localization · Mobile wireless sensor network · Range-free · Sequential Monte Carlo

1 Introduction

Mobile Wireless Sensor Network (WSNs) enables remote monitoring and data gathering in applications such as healthcare monitoring [1, 2], flood detection, target tracking [3], vehicular networks [4, 5], ambient intelligence [6], body area networks [7] routing protocols [8, 9] and creates automatic mapping [10]. In these applications, the location information is vital to ensure their reliability.

The location estimation of mobile WSNs is a complex and costly process because of the resource constraints in the sensor nodes, such as limited CPU processing capability memory, battery life, and communication range [11]. Moreover, the mobility of the sensor nodes causes its locations [12] and system topology [13, 14] to change dynamically over time.

The localization schemes are categorized as range-based or range-free [15]. In range-based schemes, additional hardware is required to find the absolute distance or angle between two sensors. However, the range-based localization schemes are costly and dissipate more energy.

Contrarily, range-free schemes can estimate a blind node location through message exchanges between nodes within an overlap area and without additional hardware. In this study, the range-free schemes are studied as they are

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more energy saving and realistic for real-world implementation as it is unaffected by the environments. The most prominent range-free schemes that effectively approximate the location of blind node are sequential Monte Carlo [16] approaches such as Monte Carlo localization (MCL) [17], Monte Carlo localization boxed (MCB) [18] and MSL* [19].

In the changing environment, three types of nodes can be derived from the topology namely, anchor node, normal node and blind node. An anchor node is a node with location information obtained either from Global Positioning System (GPS) [20] or through manual configuration, whereas a normal node establishes its location information via message exchanges with its neighbors. Additionally, a blind node is a node without location information.

Generally, the location of a blind node can be estimated either from anchor node or from a combination of anchor and normal nodes. For example, MCL estimates the location of blind node using its anchor nodes. However, the accuracy of the scheme depends on the density of anchor nodes; thus, the error of location estimation increases as the density of anchor nodes decreases. The dependency on the anchor nodes in estimating blind node can be reduced with utilization of both anchor and normal nodes as in MSL* [19]. As a result, size of sample sets and number of parameters are adapted, and energy and cost are saved. Nevertheless, MSL* approach increases the communication cost in the existing WSNs.

Therefore, Low Communication Cost (LCC) scheme for localizing mobile WSNs is proposed to reduce communication cost but maintain a localization accuracy comparable to MSL*. In the proposed LCC scheme, neighbor nodes are selected based on the number of the intersecting elements between the neighbor nodes and the blind node instead of using all the neighbor nodes as in MSL*.

The rest of this paper is organized as follows: Sect. 2 provides a review on the literature of WSN localization. Section 3 explains the proposed LCC scheme in detail. Section 4 presents the simulation results of the proposed scheme. Section 5 discusses the findings obtained from this study. Finally, Sect. 6 concludes this paper.

2 Related work

Mobile WSNs produce a large amount of data. Collecting and transmitting these, data are possible with intelligent aggregation methods and efficient routing protocols integrated into WSNs applications. However, such data without location metadata is useless. In this section, we present the related works and organize in three Sects. 2.1, 2.2 and 2.3.

2.1 Localization schemes

Location information in mobile WSNs is essential for most WSN applications. The coordinates of the sensor node embedded in the sensed message can be retrieved from the GPS [20]. However, the quality and accuracy of GPS signals depend on the environment. Obstacles, such as unfavorable indoor, underwater, and foliage conditions, can negatively affect the reception of GPS signals. Moreover, the use of the GPS is expensive and dissipates energy. Such drawbacks make the GPS inefficient for implementation in each sensor node.

Localization schemes are categorized as range-based or range-free [15]. In range-based schemes, additional hardware is required to find the absolute distance or angle between two sensors. The time difference of arrival is used in ultrasound devices [21], whereas the angle of arrival [22] is used in directional antenna arrays. Another approach employed in range-based schemes is using a received signal strength indicator (RSSI). The approach depends on the relation between the distance range from the sender to the receiver and the signal strength. RSSI has been used to find the distance between nodes within the same range [23]. Using additional hardware in range-based schemes can facilitate high-accuracy localization in an open environment but can be costly and dissipate more energy

Location estimation is a challenging task in range-free schemes and essential for most mobile WSNs applications. One of sequential Monte Carlo approaches is MCL scheme [17] that allows each blind node to gather its location information via message exchanges with the first- and second-hop anchor nodes. First-hop neighbors are nodes that can communicate directly with the blind node, whereas second-hop neighbors communicate indirectly with blind node over the first hop. Then, the MCL estimates its blind node location by averaging all sample coordinates collected from its neighboring anchors. The process of MCL is described in three steps: the initial step, the prediction step, and the filtering step. Overall, the MCL improves the localization accuracy but suffer from high density of anchor node and low sampling efficiency.

To improve the sampling efficiency in MCL, MCB [18] uses anchor boxes, which are square boundaries drawn around the anchors. The estimated location sets are constructed using random samples from the rectangle intersection area between the current time (t) and the previous time slot ($t-1$). The anchor location information set is used in both prediction and filtering steps. Although MCB effectively minimizes probability of selecting inappropriate samples, it still experiences the same localization error as in MCL and apply the same filtering constraint.

Sampling efficiency of MCB is further improves in WMCL scheme [24] by reducing the scope of bounding box, and the candidate samples are selected from the reduced area. Moreover, the WMCL uses normal nodes to improve its location estimation. However, WMCL requires higher communication and computational costs than MSL* as each normal node broadcast their location, sample set and maximum error on the x-axis and y-axis.

Orbit [25] uses a star graph that contains one root and five leaves improve the localization accuracy of blind nodes. However, Orbit is the most complex between the range-free schemes. The drawback of having to find five independent sets of nodes severely limits the feasibility and possible applications of the Orbit scheme in WSN. Moreover, the star graph with five leaves does not exist in actual WSN setups.

2.2 Coverage of WSNs (overlapping)

Ring overlapping based on comparison of RSSI (ROCRSSI) [26] manipulates the signal strength of the anchor nodes that are affected by their distances from the blind node. However, a normal node may receive consecutive samples from the same anchor in the overlap area. Accordingly, Chen et al. [27] applied a back off-based broadcast mechanism to minimize redundancy and reduce message overhead by finding a smaller hop count.

Chen and Lo [28] uses the overlap area to estimate the location of the blind nodes. The location is estimated by determining the overlap point between neighboring reference nodes (i.e., nodes whose locations are known) and blind nodes. A square is then drawn around the reference node to find an intersection rectangle containing a blind node. The overlap point is the middle point of the centers of two reference nodes. Moreover, an overlap degree that counts the coverage areas that contain overlapping points is used to reduce redundancy; as a result, the overlap points with maximum overlap degrees are averaged to estimate the blind node location.

In the scheme proposed by Sheu et al. [29], a blind node estimates its position by gathering samples from both anchor and normal nodes whose positions are evaluated from anchor node samples. The distance between normal nodes is used to select samples by narrowing the overlap region between normal nodes. Therefore, if the distance is long, the communication cost decreases; conversely, if the distance is short, the communication cost increases because a large overlap area between normal nodes results in unnecessary and redundant messages. Moreover, the scheme can estimate the movement direction of the nodes to reduce the localization error.

Comparing the overlap area with a predefined threshold value is another approach to reduce communication cost in the overlap area [30]. When the distance value is greater than the threshold value, a localization message can be transmitted. By contrast, when the distance value is less than the threshold value, the message cannot be sent. The size of the overlap area and the degree of overlapping must be considered to ensure the accuracy of the estimated location and communication costs [28].

2.3 Challenges and issues in WSNs

Nodes in WSNs communicate and cooperate with each other to present the real and current states of the system. Thus, utilizing a large number of sensors will produce a large amount of data. In this case, aggregating and forwarding such data to the sink node in real-time will be challenging [31–33]. For example, long transmission path and congestion will result in delay. Such delay can destroy a significant amount of data and impractical for implementation in critical systems such as healthcare [34–36], firefighting and flood detection. Moreover, sending a large number of data requires a great deal of power. Therefore, to secure a successful transmission of a large data in WSNs, an effective data compression method is needed [37].

Routing protocols used in traditional network are incompatible with WSNs. This is due to hardware limitations in sensors namely, small processors, small memories, limited communication range and limited power resources [38, 39]. Furthermore, battery life is short and in most applications, changing the battery is not easily done. Thus, to mitigate the hardware limitations in sensors, the routing protocols must be designed to be precise, intelligent, lightweight and energy efficient [40–42]. Additionally, the designed routing protocols must consider robustness and scalability factors in networks.

Another interesting challenge in WSNs is the realization of WSNs as an intrinsic part of Internet of Things (IoT). This allows the sensors to collect the data from physical areas and connecting it with IoT elements [43]. The communication between sensors and IoT elements are established through TCP/IP routing protocols. However, the implementation of TCP/IP routing protocol in sensor is restricted, as sensor has limited resources [44]. Achieving the full potential of WSNs in IoT require the issues such as security and privacy [45], trust management and scalability [46] to be addressed. These issues remain a challenge and need to be explored further to improve the utilization of WSNs in our daily life.

3 Proposed LCC scheme

This section explains the proposed LCC scheme, an improvement of previous MSL*, that aimed at reducing the communication costs. The normal nodes are utilized to construct the location information set of the blind nodes in a mobile WSN.

3.1 MSL* scheme

MSL* estimates a blind node location through a set of weighted samples drawn from neighboring anchor and normal nodes. The quality of a sample is based on its weight. The samples with high weights are chosen to estimate a blind node location. Anchor nodes always have high weights, whereas normal nodes have partial weights ranging from 0 to 1. MSL* location estimation is divided into three stages.

Initial stage: In this stage, sensor nodes are distributed randomly in the area. The sample set is constructed randomly from the whole area. The samples are then weighted according to the anchor node samples within their range.

3.1.1 Sampling stage

The movement of the nodes per time slot is based on the following transition equation:

$$p(S_t|S_{t-1}) = \begin{cases} \dfrac{1}{\pi(V_{\max}+\alpha)^2} & if\ d(S_t, S_{t-1}) \le V_{\max} \\ 0 & if\ d(S_t, S_{t-1}) \ge V_{\max} \end{cases} \quad (1)$$

where ($V_{\max}$) represents the maximum speed of the node from point to point and d (S_t, S_{t-1}) represents the distance between nodes at time (t) and the previous time ($t-1$). In each time slot, a new sample set is constructed randomly within a circle radius ($V_{\max}+\alpha$) centered at the coordinates of a previous sample. For a static case, parameter α with a value of $\alpha = 0.1\ R$, where R is the circle radius of the transmission range, is used.

3.1.2 Resampling stage

In this stage, the elements of the current sample set are reconstructed based on the sample weight. Samples with high weights are retained, whereas samples with low weights are removed.

The weight of a node sample is based on the location estimation of its neighbors. A node selects neighbors according to their closeness values. Closeness is the average of the distances between all valid samples and the estimated blind node location. The closeness value for the anchor node is always 0, and the closeness values of the normal nodes are between 0 and 1.

$$closeness_p = \frac{\sum_{i=1}^{N} W_i \sqrt{(x_i - x)^2 + (y_i - y)^2}}{N} \quad (2)$$

where N is sample number of node p, (x_i, y_i) are the i-th sample coordinates (i = 1, …, N), (W_i) is sample weight, and (x, y) is estimated location of node p at the current time.

3.2 Proposed LCC

The proposed approach is expected to have a localization accuracy comparable with that of MSL*. Additionally, LCC has a major advantage over MSL*, that is, lower communication costs across different parameter ranges.

The LCC scheme presents normal nodes in an adjacency matrix. Relations between normal nodes can be classified into three types, namely, out of range, the neighbor in the first hop, and the neighbor in the second hop, whose values are 0, 1, and 2, respectively. In adjacency matrices, each normal node has a row containing their neighbors, and this row can be considered a set. The intersection between the blind node set and its neighbor's sets is employed to select a normal node that shares more neighbors with the blind node set to find the intersecting elements. Neighbors with less than average intersecting elements are considered out of range in the adjacency matrix. The adjacency matrix is a simple matrix that represents the graph vertices according to whether two nodes are adjacent (i.e., have an overlap area).

Figure 1 presents an example of LCC scheme. The nodes are labeled with an identity number (id). The blind node has a set of neighbors, $B = \{0, 1, 6, 7, 8, 9\}$, and the numbers of the intersecting elements between the blind node set and its neighbor sets are two, five, two, three, four, and four, respectively. For example, the intersecting elements between the blind node set, $B = \{0, 1, 6, 7, 8, 9\}$, and the neighbor set with (id = 0) = {1, 3, 4, 5, 8} is two, $B \cap$ (id = 0) = {1, 8}.

The average number of the intersection elements between the blind node and its neighbors is three. Nodes (id = 0, 6) have intersecting elements that are less than the average, thus, the relations of both nodes with the blind node are considered out of range. A low number of

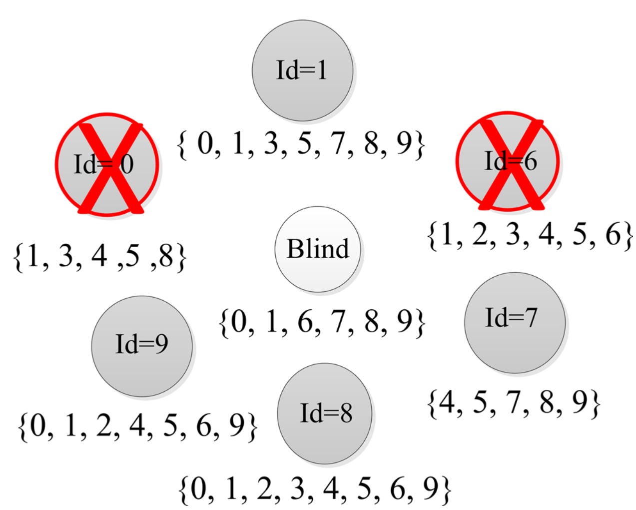

Fig. 1 Example of selecting normal nodes based on the LCC scheme

intersecting elements indicate that the two nodes are far away. The number of common neighbors between two nodes can be used to measure the closeness between them [47].

LCC improves MSL* by drawing an estimated location set from both anchor and normal nodes. It selects a number of normal nodes within the first- and second-hop neighbors. LCC selects a number of normal nodes in neighbors to achieve localization accuracy with minimum dependency on anchor nodes and lower communication cost. The selection is based on the intersecting elements between the blind node set and its neighbor sets and unlike in MSL* which considered all neighboring normal nodes.

3.3 Differences between LCC and MSL*

The main idea of MSL* [19] is to estimate the location of blind nodes by drawing samples from the anchor nodes and all normal nodes among the first-hop and second-hop neighbors. Normal nodes are used to improve localization accuracy and reduce dependency on the anchor nodes. The use of all normal nodes in MSL* increases communication cost without improving location estimation accuracy due to redundant and low-weight samples.

In the filtering stage, MSL* uses a closeness value to weight samples. A low closeness value indicates that the node has a low localization error. Thus, the blind node can use the closeness value to weight its samples. The use of closeness values can minimally reduce communication cost in the filtering stage when high-weight samples are selected. The LCC scheme can reduce communication costs by selecting normal nodes that share a more neighbors with a blind node before the location estimation process, which starts by redefining the relation between a blind node and its neighboring normal nodes.

4 Evaluation

In this study, MCL, MCB and MSL* are simulated using the simulator code obtained from Hu and Evans [17], Aline Baggio [18] and Rudafshani [19], respectively. The proposed LCC is implemented in MSL*, and the original parameters are retained.

4.1 Experimental parameters

The proposed scheme is tested in a simulation executed 50 times. The location estimations of all sensors were reset to the same values in each simulation. The parameters in LCC were set to the same values as those parameters in MSL*. Sensor nodes were randomly distributed in a bounded square of 500 units $\times$ 500 units. The radio transmission range for all nodes was set as a perfect circle with a radius (R) of 50 units. The node density (N_d) is the mean density of the normal nodes and the anchor nodes in the neighborhood of a node, whereas the anchor node density (A_d) is the mean density of the anchor nodes in the neighborhood of a node. In our experiment, $N_d = 10$, $A_d = 1$, $V_{max} = 0.20\ R$, and the number of sample sets was 50 unless otherwise specified. Sensors move according to a modified *waypoint* model [48] in which the time paused is 0 [11, 49].

4.1.1 Node communication

WSN location is constructed from a set of nodes N, which are distributed randomly in a two-dimensional *Euclidean* space (E2). The space is presented as a bounded flat surface area in E2 if any boundary exists. When nodes overlap with each other, the Euclidean distance d (node g, node h) between each pair of nodes can be derived by applying RSSI [23, 26]. The node coordinates are a pair of dimension axes using the values x and y. Each sensor has a full circle of radio range with a radius R. However, a sensor can also use a heterogeneous radio range.

In the initial stage, sensor nodes are spread randomly throughout the network region E2. The node movements per time slot according to the modified random waypoint mobility model [48, 49] are used in MCL and MSL*. In a waypoint model, the movement direction and speed of a node in a time slot are considered. Time is divided into static slots and has the maximum speed (V_{max}); speed varies from 0 to V_{max}.

4.2 Simulation results

In this section, LCC, MSL*, MCB and MCL are compared at different network settings. The simulation results are presented in two sections: accuracy and communication costs.

4.2.1 Accuracy of LCC

Convergence of LCC The variation in the convergence of LCC at various speeds and anchor node densities is presented in Figs. 2 and 3. The location estimation error decreases in all cases until the error converges; the error slightly changes around a constant value. The error under a static condition rapidly converges because the node has the same location when it receives a new observation. Mobile sensors change locations per time unit, and new observations can be drawn from each of these locations. A new observation can improve localization accuracy and reduce localization error. This concept is suitable for low- and medium-speed observations with an exception for high-

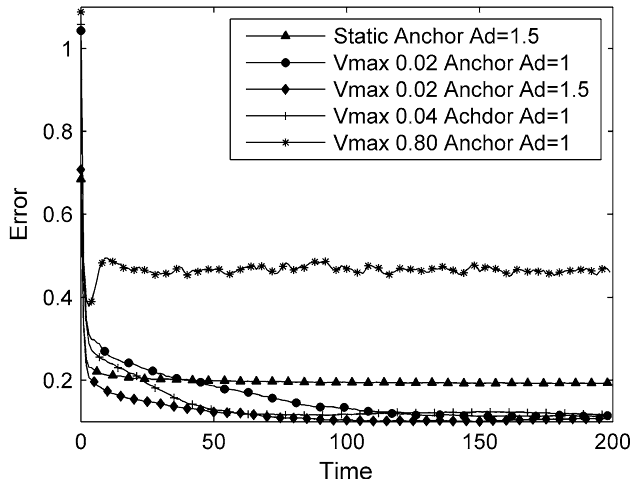

Fig. 2 Localization error and speed values of LCC in different mobility cases

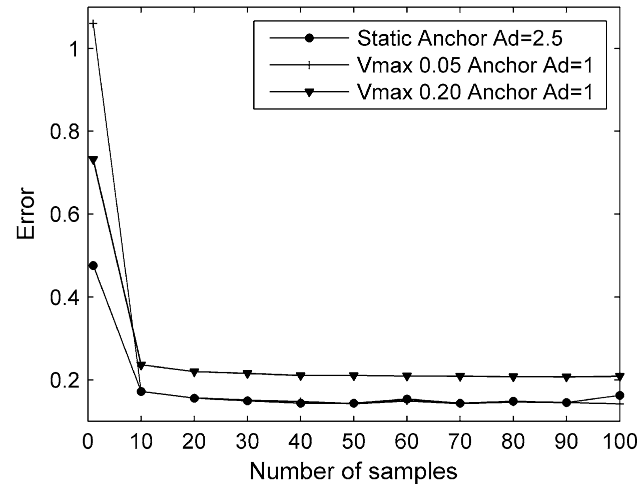

Fig. 4 Effect of sample size in LCC

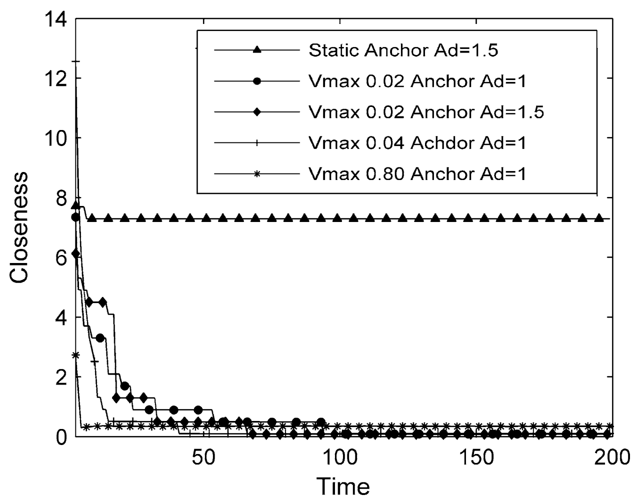

Fig. 3 Relation between closeness and speed of LCC in different mobility cases

speed observation. Thus, the observation in the previous time step does not improve the localization of high-speed moving sensors.

In our experiment, the localization error and the value of closeness have quickly converged because the LCC scheme received samples from normal nodes with more neighbors the same as those of a blind node. This result validates the concept presented in Sect. 3, that is, selecting normal nodes that share more neighbors with a blind node reduces localization error and communication costs.

4.2.1.1 Effect of sample size A *Monte Carlo* localization technique using the average of valid samples is employed to estimate the locations of blind sensors. A considerable number of valid samples require more memory and computation time; however, a low number of samples are inadequate to estimate the blind sensor location. Therefore, the optimum number of samples should be obtained to estimate the blind sensor location [30]. Through simulation, LCC is implemented using various numbers of samples, as shown in Fig. 4. From the LCC simulation results and the results of MCL, MCB and MSL*, 50 samples is considered adequate in estimating a blind node location in LCC, MCL, MCB and MSL*.

4.2.1.2 Effect of sensor node speed Figure 5 shows the simulation results of LCC, MSL*, MCL and MCB at different sensor node speeds. The movement of the sensors can improve localization accuracy by visiting more areas, increasing observations, and obtaining new samples. However, when sensors move at a high speed, the location information at the previous time is no longer applicable. Thus, the localization error increases.

Figure 5 shows that the optimum maximum speed for LCC, MSL*, MCL and MCB schemes is 0.20 *R*. Thus, this value is used as the default setting in the present experiment unless another value is assigned.

4.2.1.3 Effect of normal nodes density The simulation results presented in Fig. 6 are obtained when the node density varies whereas the anchor node density is fixed. The location estimation error in MCL and MCB decreases with an increase in normal node density. This reduction in location estimation error is twofold in LCC and MSL* with an increment in normal node density. Each blind node in LCC and MSL* has more neighboring normal nodes in their first and second neighborhoods. Thus, a blind node obtains more location information; consequently, the location estimation error is reduced.

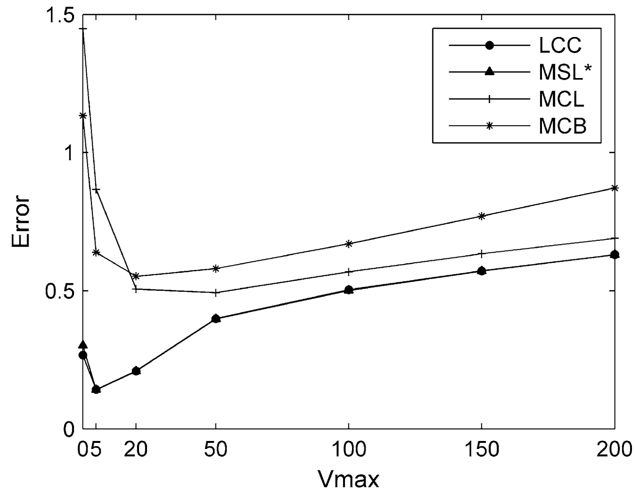

Fig. 5 Effect of the sensor node speed on localization

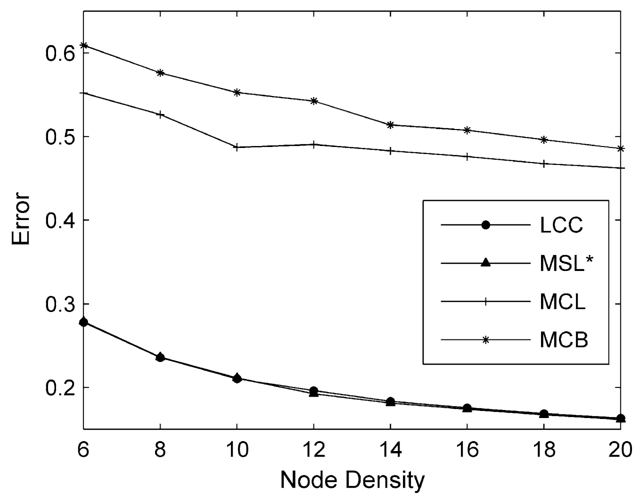

Fig. 6 Effect of normal node density

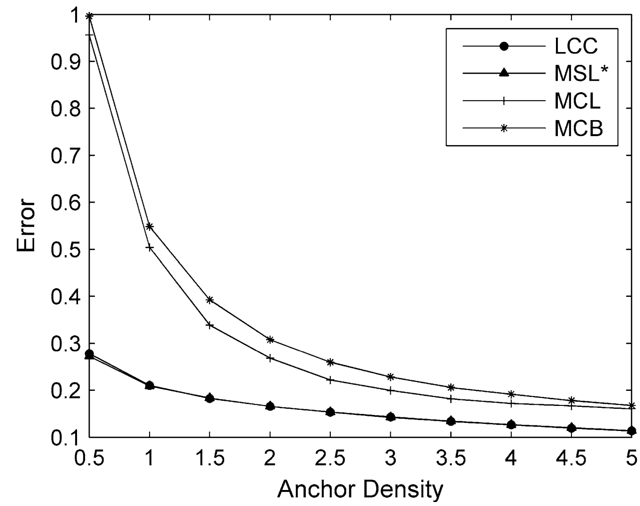

Fig. 7 Effect of anchor node density

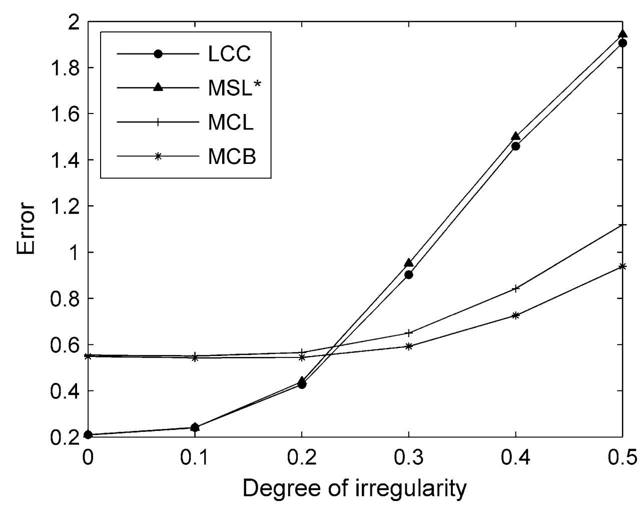

Fig. 8 Effect of degree of irregularity

4.2.1.4 Effect of anchor node density In Fig. 7, the anchor node density increases, whereas the normal node density is constant. Increasing anchor node density per time slot has affected the performance of all schemes. MCL and MCB benefits the most from this increment because both MCL and MCB only uses anchor location information to determine a blind node location. LCC and MSL* are less affected by anchor node density than MCL and MCB because they both normal and anchor nodes are used in LCC and MSL* to estimate a blind node location. As shown in Fig. 7, the simulation results demonstrate that using a small number of anchor nodes in the LCC is sufficient to estimate a blind node location.

4.2.1.5 Effect of irregularity in radio range Using perfect circles denoted by R in radio transmission during the simulation cannot express the actual value of radio transmission. Therefore, the degree of irregularity (DOI) is applied to measure the variation in the range and direction of radio transmission. For example, the actual range and direction of radio transmission can randomly vary within the range [0.7 R, 1.3 R] when DOI $= 0.03\,R$. The variation in DOI obtained in the simulation is depicted in Fig. 8, which indicates that a high variation in the range and direction of radio transmission can increase localization errors. The simulation results show that all schemes are negatively affected as DOI increases. Thus, in the real-world implementation of WSN, DOI is more critical than other obstacles due to environmental conditions and antenna irregularities.

4.2.2 Communication cost of LCC

Communication overhead is measured according to the number of messages sent by a sensor in each step of location estimation [17]. The number of messages varies across location estimation schemes. The number of messages sent in both MCL and MCB is equal to the number of anchor nodes while in MSL* is equal to the number of anchor and normal nodes multiplied by the sample number, which is by default 50 samples in this study. The number of messages sent in LCC is set to the total number of anchor and normal nodes that have more common neighbors with a blind node. Thus, the number of messages sensor nodes should send is reduced in LCC.

Figure 9 shows the correlation between the normal node density and the number of messages sent. The LCC scheme has a lower number of messages sent than MSL* as the node density increases. In the total, LCC sends a lower number of messages at a time than MSL*, as shown in Fig. 10. In both Figs. 9 and 10, both MCL and MCB are excluded in the analysis of number of messages sent because of an inaccurate comparison. As the number of messages sent by MCL is equal to the number of anchor nodes only, MCL and MCB will always generate the smallest number of messages sent at all times.

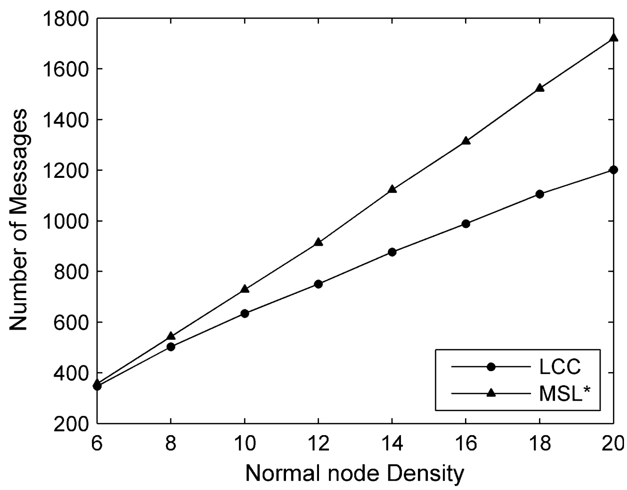

Fig. 9 Effect of normal node density on the number of exchanged messages in the LCC and MSL* schemes

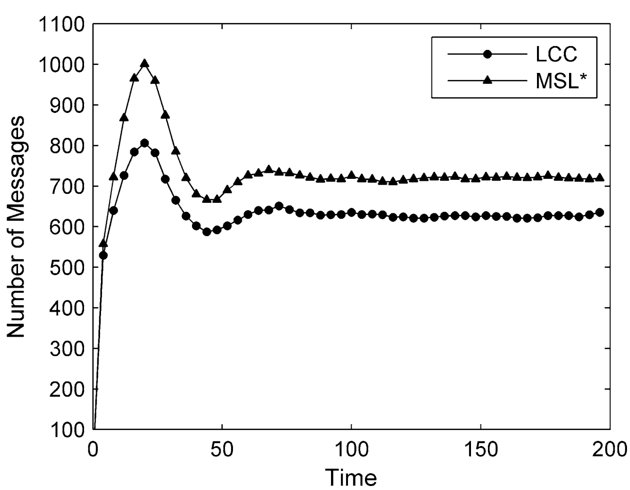

Fig. 10 Number of exchanged message sent in speed 0.2 *R*

Resources, memory, and processing time are required each time a message is sent in the networks. The computation and communication costs are low if the number of messages is minimal. According to the results, a small number of messages are sent over time in LCC. Therefore, LCC is expected to reduce communication costs, save energy, and work with manageable resources.

5 Discussion

The main concept of the LCC scheme is to use a normal node instead of relying solely on anchor nodes to improve location estimation. This scheme works by discovering more overlapping areas to improve localization accuracy. Therefore, a blind node can construct its location estimation set from both anchor and normal nodes within the overlap area. A large overlap area will negatively affect the location estimation accuracy. This condition is particularly observed when all normal nodes are used in localizing a blind node position. When a small number of normal nodes are employed, the small overlap area is insufficient for drawing samples.

In this study, we used normal nodes to estimate a blind node location beside a limited number of anchor nodes as in the MSL* scheme. However, MSL* requires high communication cost. Therefore, we improved the MSL* by selecting a number of normal nodes that is close to a blind node. Then, we find their closeness value through the number of common neighbors between a blind node and its neighboring normal nodes.

In all simulation scenarios, the accuracies of LCC and MSL* in locating the blind node are comparable. However, LCC entails lower communication costs because a lower number of messages are sent over time. The sample size, speed, anchor node density, normal node density, and degree of irregularity mainly affect localization accuracy in mobile WSNs.

Drawing a sufficient number of valid samples is critical for the Monte Carlo scheme. However, drawing a high number of samples requires more energy without improving the accuracy. Therefore, a simulation is performed to find the optimum number of valid samples. The simulation results show that a sample size of 50 samples is the optimum; thus, it was the default value used in MCL, MCB, MSL*, and LCC. Moreover, the simulated results show that even a limited number of samples are sufficient in LCC to estimate a blind node location accurately.

Mobile sensors can receive more observations; thus, localization accuracy can be increased by visiting new areas. However, this mechanism holds true only if the mobility of the node is at low and medium speeds. Therefore, improving the accuracy of LCC in high-speed cases can be explored in future studies.

The variation in anchor node density has minimal effect on MSL* and LCC because both used normal and anchor nodes to estimate a blind node location. By contrast, MCL and MCB are significantly affected as the density of the anchor nodes decreases because of the high dependency on anchor nodes when estimating a blind node location.

Increasing normal node density has improved localization accuracy of blind nodes and reduced dependency on anchor nodes. In MSL*, each normal node needs to send its samples in each time step. Therefore, the number of samples sent is highly affected when normal node density increases. The number of samples sent is reduced by selecting the closest normal nodes to estimate a blind node location. The selection reduces communication costs but maintains the same localization accuracy in all cases. Communication cost (i.e., the number of messages sent) is reduced by a minimum of 0.02, a maximum of 0.30, and an average of 0.18 at different normal node densities ranging from 6 to 20.

The degree of irregularity affects all schemes. A slight irregularity in the range and direction of radio transmission can easily increase localization error. By contrast, more controlled increments in errors are observed in MSL* and LCC. Both schemes increase the number of overlapping areas and the size of the overlap area to accommodate the variation in the range and direction of radio transmission.

6 Conclusions

The proposed LCC for mobile WSNs is a range-free localization scheme that reduces communication costs and maintains a location estimation accuracy comparable with that of MSL*. The LCC scheme selects normal nodes that share more neighbors with a blind node. The results show that the use of normal nodes improves localization accuracy and reduces communication cost and dependency on anchor nodes. We will implement this novel scheme in a real-life experiment in our future work.

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