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Weighted Localization in Mobile Wireless Networks

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Summary

Localization of wireless devices is a crucial requirement for many emerging applications such as environmental monitoring, intelligent transportation, home automation, health-care monitoring and social networking. In this letter, we propose AWL a new Aggregate Weighted Localization algorithm for mobile wireless networks. The proposed algorithm is distributed and requires low computational and communication overheads enabling its use in resource-limited devices.

KEYWORDS:
Mobile wireless networks, distributed localization, aggregate metrics, weighted average

1 | INTRODUCTION

Location awareness is an essential feature for many applications of mobile wireless networks. Indeed, the information collected or communicated by the wireless mobile nodes is usually valueless without the knowledge of the nodes location. Location information also enhances the interaction between the nodes and their surroundings. Mobile wireless nodes could be equipped with a global positioning system (GPS) to obtain their locations, but this is currently a costly solution (energy consumption, production price, size of the node). Besides, GPS service may be inaccessible in some environments such as mountains, dense forests and indoors [1]. Thus, in the recent years, several localization algorithms that aim at obtaining nodes locations with low costs have been proposed. In such algorithms, a small set of nodes with known positions (called anchors or reference points) advertise their locations in order to assist nodes with unknown locations (called unknown or normal nodes) to estimate their coordinates [2].

Paper [3] proposed the Centroid Localization (CL) algorithm. In CL, the estimated location of an unknown node is calculated as the centroid of the coordinates of beacon nodes within its communication range. Instead of using the coordinates of all in-range beacons, in [4] an unknown node first collects the Received Signal Strength (RSS) of all the nearby beacons, selects those whose RSS is above a given threshold and finally estimates its location as the average of these chosen beacons. One big issue with centroid localization techniques [5, 6] is that they assume that all the selected reference points are equally proximate to the unknown node [7]. Since such an assumption is usually not satisfied in practice, the authors of [8] introduced the Weighted Centroid Localization (WCL) algorithm where each reference point is attributed a weight depending on its distance to the unknown node. The weight of the i^{th} reference point is equal to $\frac{1}{(d_i)^g}$, where d_i is the distance between the unknown node and the i^{th} reference point and is estimated through the RSS received from the reference point, $g > 0$ is a parameter that determines how much the distances affect the weight function. Increasing the value of g increases the weight of the closest reference points. Many recent works have adopted the WCL approach [9, 10]. However, most of the proposed WCL approaches exclusively rely on a single metric, and especially the RSS, to weight the collected location information. Depending on a single metric can nevertheless result in poor position estimations particularly when the considered metric is not sufficiently reliable (RSS is unstable in real environments). Combining several measures from different categories would provide better performances than just relying on a single metric.

The work in [11, 12, 13, 14] propose Monte Carlo Localization (MCL) algorithms. In MCL techniques each unknown node maintains a set of weighted samples representing its possible positions and estimates its position as the weighted average of these samples. In [11], each node uses the positions of its neighboring anchors to weight its samples. The weight of each sample is either 0 or 1. Relying only on the anchors location information requires an increased anchor density in order to achieve reliable location estimates. Anchor nodes are yet generally more expensive and are deployed in much lower densities than normal nodes. It will therefore be very advantageous if the estimated locations of the normal nodes can also be used to improve the localization accuracy. The work in [12] extended [11] by using the location estimates of non-anchor neighbors and

not just anchor nodes. Nodes use only the information of normal neighbors that have more accurate estimates than theirs. The quality of a position estimate is measured using a parameter called *closeness*. The work in [13] uses a bounding-box that improves the sampling efficiency by reducing the scope from which the samples are selected. To estimate the unknown nodes locations, the proposed algorithm uses 1-hop neighboring anchors and normal nodes as well as the 2-hop neighboring anchors location information. Considering 2-hop beacon broadcasting may ameliorate the location estimations but will on the other hand increase the communication costs particularly in high density networks. The major disadvantages of MCL techniques is that they require the knowledge of the nodes radio ranges and assume that nodes are synchronized and can send and calculate their location information at the same discrete time step. In real environments, the radio ranges are nevertheless constantly changing due to different factors including the nodes residual energy and surrounding environment. Besides, time synchronization is generally a difficult task to achieve in wireless networks. Finally, the synchronized sending of location information increases the probability of packets collisions and hence the loss of the location information.

Paper [15], proposes a cooperative localization technique divided into two phases : a start-up phase and a refinement phase. The start up phase addresses the sparse anchor nodes problem. In this phase, nodes cooperate to spread (hop-by-hop) the anchor nodes positions throughout the whole network, allowing as such every unknown node to have an initial coarse position. In the refinement phase, normal nodes iteratively ameliorate their initial positions by using their 1-hop neighboring normal nodes estimations. Each normal node is attributed a weight reflecting the quality of its estimation. Like most of the flooding-based techniques, this algorithm have a very high communication overhead and suffers from severe contention, which can significantly degrade its performance. Cooperation among nodes can increase the position accuracy at the cost of higher energy consumption. To reduce such an overhead, paper [16] uses a game theoretical approach while [17] proposes a hierarchical approach where nodes are gradually activated to estimate their positions. Papers [18, 19] assume that anchor nodes are able to dynamically increase their transmission power in order to ameliorate positions estimation. Increasing the transmission power results in two drawbacks. One is that the anchor nodes are required to have more energy than the rest of the nodes, and a second is that the higher transmission power increases the interference among the network nodes. The work in [20] proposes a hybrid system that combines inertial measurements from a smartphone with RSS measurements in order to determine the position of a pedestrian. Experiment results have shown that the use of the RSS in conjunction with the inertial measurement of a smartphone can improve the accuracy of the position estimation. The problem of this work is its restrictive applicability to indoor pedestrian scenarios.

Taking into consideration the drawbacks of the previously proposed localization techniques, we propose a localization algorithm that (1) does not require the synchronization of nodes (2) aggregates different metrics of different types in order to weight the received location information providing as such a better reliability and robustness against the uncertainty of certain metrics (3) does not require the knowledge of the nodes radio transmission range (4) requires a low computational cost (basic mathematical operations) and a low communication overhead (1-hop messages broadcasting). The remaining of this letter is organized as follows. Section 2 presents AWL our novel weighted localization algorithm. Section 3 uses simulations to evaluate the performance of AWL and compare it with existing localization techniques. Section 4 concludes the letter.

2 | AGGREGATE WEIGHTED LOCALIZATION ALGORITHM

In this section, we present our proposed algorithm. We first detail how a normal (unknown) node calculates its aggregate weighted location. Particularly, a normal node uses a set of basic mathematical operations with a low computational cost such as additions, subtractions and multiplications. We then describe the behaviour of both anchor and normal nodes within the network. Nodes rely only on 1-hop communication (no flooding) which minimizes the communication overhead.

Location estimation: The system consists of three categories of nodes: fixed anchor nodes, mobile anchor nodes and mobile normal (unknown) nodes. Both anchor and normal nodes broadcast messages with their location information. A location information message is as follows: *Loc_msg(*ID, (x,y,z), v, a, ε). ID is the identity of the sender; (x,y,z) is the location estimate of the sender; v is the velocity of the sender; a is set to 1 if the message sender is an anchor and to 0 if the message sender is a normal node. The parameter ε describes the quality of the sender location estimate. The higher is ε the better is the quality of the location estimation. Each normal node maintains a location information table (*Loc_tab*) in which it stores the received location information. A normal node updates its location information table for each received location information message: once a location information message is received, the normal node first estimates the distance to the sender d, the distance estimation error Δ, the link quality Q and then records them along with the received location information message and the time of the reception of the message t_r in the location information table. At any time, a normal node can estimate its location as the weighted average of the coordinates of the recorded location information, as shown in equation (1). $L_i(x,y,z)$ is the i^{th} recorded location information, w_i is the weight of $L_i(x,y,z)$ and n is the number of the recorded location information. The weight w_i of the i^{th} location information entry is, as shown in equation (2), the aggregation of five different weights w_{i1}, w_{i2}, w_{i3}, w_{i4} and w_{i5}. Such an aggregation provides a better reliability and robustness against measurement errors [21].

$$P(x,y,z) = \frac{\sum_{i=1}^{n} w_i L_i(x,y,z)}{\sum_{i=1}^{n} w_i} \quad (1)$$

$$w_i = \frac{\alpha_1 w_{i1} + \alpha_2 w_{i2} + \alpha_3 w_{i3} + \alpha_4 w_{i4} + \alpha_5 w_{i5}}{\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 + \alpha_5} \quad (2)$$

The weight w_{i1} depends on the source (sender) of the location information. As shown in equation (3), the location information collected from normal nodes is attributed lower weights than that received from anchor nodes. These weights depend on the location estimation quality ε. The weight w_{i2} depends on the freshness of the stored location information and is calculated using equation (4), where T is the maximum time that a received location information can be stored in the location information table; τ_i is the duration of time that the i^{th} location information has been stored. As shown in equation (4), w_{i2} is inversely proportional to τ_i. Fresher information is hence attributed higher weights. The weight w_{i3} depends on the receiver/sender separating distance and is calculated using equation (5), where d_i is the estimated distance separating the i^{th} state information sender and the normal node when the location message was sent and Δ_i describes the distance estimation error. The variable Δ_i can be set to zero if the distance estimation error can not be evaluated. The weight w_{i3} is inversely proportional to the distance; the location information received from closer nodes is consequently attributed higher weights. We note that our algorithm does not depend on a specific ranging technique. Nodes can use any available range measurement technique such as the Time Of Arrival (TOA) or the Received Signal Strength (RSS). The weight w_{i4} depends on the mobility of the sending node and is calculated using equation (6), where v_i is the velocity of the sender of the i^{th} recorded location information and v_{max} is the maximum velocity within the recorded velocities. As we can see from equation (6), w_{i4} is inversely proportional to the velocityof the sender. We attribute higher weights to the location information received from slower nodes. The weight w_{i4} is particularly needed in networks with high propagation delays. In such networks, the sending node position may, depending on its velocity, has considerably changed when the message is received. The weight w_{i5} depends on the link quality between the i^{th} location information sender and the receiver and is calculated using equation (7), where Q_i quantifies the link quality between the sender of the i^{th} recorded location information and the receiver, Q_{max} is the maximum link quality within the recorded link qualities. The weight w_{i5} is proportional to the link quality. We attribute higher weights to more reliable links. Nodes can use any available link quality estimation technique such as the Packet Reception Ratio (PRR), the Received Signal Strength Indicator (RSSI) or the Signal to Noise Ratio (SNR). The parameters α_1, α_2, α_3, α_4 and α_5 are set to either 1 or 0 depending on the availability of the corresponding information offering hence different configuration possibilities.

$$w_{i1} = \begin{cases} 1 & \text{if the sender is an anchor} \\ \frac{\varepsilon}{1+\varepsilon} & \text{if the sender is a normal node} \end{cases} \quad (3)$$

$$w_{i2} = \frac{T}{T+\tau_i} \quad (4)$$

$$w_{i3} = \frac{\frac{1}{d_i+\Delta_i}}{\sum_{j=1}^{n} \frac{1}{d_j+\Delta_j}} \quad (5)$$

$$w_{i4} = \frac{v_{max}}{v_i + v_{max}} \quad (6)$$

$$w_{i5} = \frac{Q_i}{Q_{max}} \quad (7)$$

$$\varepsilon = \frac{\sum_{i=1}^{n} w_i}{n} \quad (8)$$

To estimate its position, a normal node first determines the maximum velocity v_{max} and the maximum link quality Q_{max} within all the recorded velocities and link qualities. Then, for each stored location information i, it uses equations (3), (4), (5), (6), (7) and then (2) to estimate the weight of the considered location information entry. The normal node finally uses equations (1) and (8) to estimate its location and the location estimation quality ε.

Location information sharing: Anchor nodes periodically broadcast (each T_a) their location information. They also broadcast their location upon the reception of a location request message from a normal node. Normal nodes are continuously collecting location information messages sent from neighbouring nodes. If the localization is triggered (due to a given event or elapsed timer) at a given normal node u, then u uses the already collected location information to estimate its location. If this estimation does not satisfy a given requested quality ($\varepsilon < \varepsilon^*$) then, in order to ameliorate its estimate, node u broadcasts a location request message (*Req_msg*) including its identity and the quality of its current estimate. Normal nodes receiving such a request, estimate their location and the quality of their estimation and respond to this request only if their location estimate quality is better than the location estimate of the requester. Anchor nodes receiving the location request automatically respond by sending their position. The requesting node u collects the answers to its request and then estimates its location. Node u finally broadcasts its estimated position if it satisfies a given quality ($\varepsilon > \varepsilon^{**}$). Both ε^* and ε^{**} are parameters to fix.

3 | PERFORMANCE EVALUATION

In this section, we use simulations to evaluate the performance of our proposal and compare it the classic Centroid Localization (CL) [3], Weighted Centroid Localization (WCL) [8] and the cooperative localization algorithm proposed in [15] which we will refer to as CoopLoc.

Simulation setup: Our simulations were conducted using the OMNeT++ simulator [22]. For all our experiments, nodes evolve in a square area of $50m$ x $50m$. Fixed anchors are randomly placed using a uniform distribution. We use the random waypoint mobility model with fixed speed and no pause time [23] for the mobile anchors and real world human mobility traces [24] for the normal nodes. The number of normal mobile nodes is fixed to $N = 19$. We adopt the simple path loss signal propagation model [25] under which the received signal strength P_r is expressed as:

$$P_r = \left(\frac{\lambda}{4\Pi}\right)^2 \cdot \left(\frac{1}{d}\right)^{\alpha} \cdot P_t \tag{9}$$

Where P_t is the maximum transmission power, d is the distance separating the sender and the receiver, α is the path loss coefficient, $\lambda = \frac{c}{f}$ is the wavelength of the transmitted signal (c is the speed of light and f is the frequency of the transmitted signal). The path loss coefficient α depends on the propagation environment. In our simulations we set α to 4, which corresponds to a non-line-of-sight indoor environment [26]. The maximum transmission power P_t is set to -34.1dbm resulting in a maximum transmission range of $14m$. The nodes communicate with each other using the IEEE 802.11 standard. The parameter g of the WCL algorithm is set to 3 as it is the most widely used value in literature [27]. Anchors broadcast their location information every $3s$. The parameters of our algorithm are set as follows: $T = 7s$, $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_5 = 1$, $\alpha_4 = 0$, $\varepsilon^* = \varepsilon^{**} = 0.8$. We use the RSSI as the link quality indicator. The distance separating a sending and a receiving node was roughly approximated through the RSS received from the sending node. The distance estimation error Δ was set to zero for all the nodes (i.e., the distance estimation errors are unknown). Each simulation scenario lasts 1 hour and was repeated up to 100 times (with different pseudorandom number generator seeds) in order to reach a confidence level of 95%.

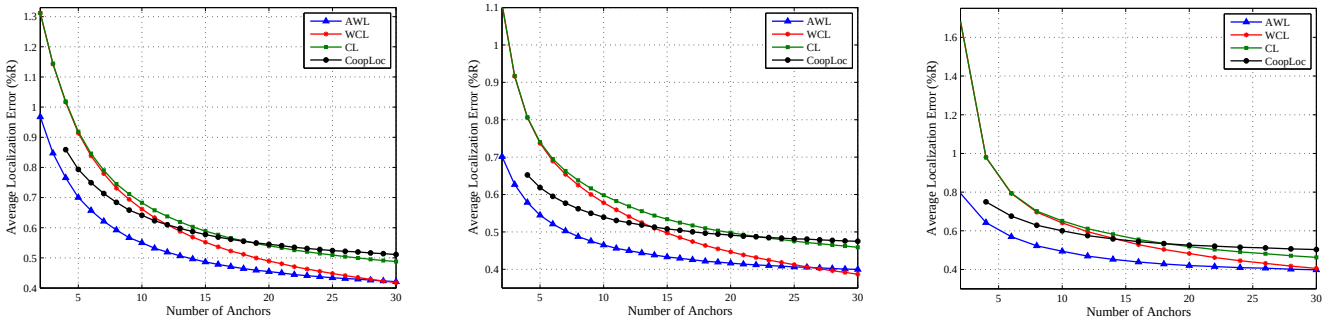
Simulation results: **FIGURE** 1 shows the average localization error obtained under AWL, WC, CL and CoopLoc. For AWL, WCL and CL we vary the number of anchors from 2 to 30. CoopLoc considers a network with a minimum of 4 anchor nodes, we hence vary the number of anchors from 4 to 30. We consider three different scenarios: (a) all anchors are mobile with a velocity $v = 1m/s$ (b) all anchors are mobile with a velocity $v = 5m/s$ (c) a heterogeneous network were 50% of the deployed anchors are static and 50% are mobile with a velocity $v = 5m/s$.

FIGURE 1 clearly shows that the location accuracy of our algorithm outperforms that of the other algorithms. Unlike WCL and CL that rely only on the location information received from anchor nodes in a given time instant, our algorithm uses the location information received from both anchor and normal nodes within the hole time period T and attributes them weights depending on different metrics including their freshness and accuracy. This enables AWL to provide much more accurate location estimations than WCL and CL particularly when the number of anchors is low (i.e., when the location information is scarce). In AWL normal nodes are continuously collecting location information messages sent from neighbouring nodes. If the localization is triggered at a given normal node u, then u can immediately use the already collected location information to estimate its location. In CoopLoc, on the other hand, a normal node needs first to collect the location information that is flooded through the hole network to have an initial coarse location estimation and then iteratively ameliorates this estimation using its neighbouring normal nodes estimations. This iterative two-phase process and particularly the flooding process introduces long delays leading to the mislocalization of the mobile nodes.

The performance of CL and WCL are similar under a small number of anchors. For a large number of anchors, the accuracy of CL deteriorates in comparison with that of WCL. This is because, CL neglects the ranging information assuming that all the anchor nodes are equidistant from the unknown node. Nodes close and far from the true location are equivalently included in the averaging procedure, thereby corrupting the estimates. When comparing the cooperative localization algorithm CoopLoc with that of the non cooperative techniques CL and WCL, we can see that CoopLoc outperforms CL and WCL under low number of anchors. Indeed, in cooperative localization, inter-nodes communication removes the need for all normal nodes to be within the communication range of multiple anchors; thus high anchor density is not required. When the number of anchors increases, the performance of CL and WCL outperforms that of CoopLoc. This is because, whith higher number of anchors, the unknown nodes are within the communication range of a sufficient number of anchors. The inter-nodes communication (and particularly the location information flooding in CoopLoc) is more burdensome (greater contention and packet loss) than beneficial.

4 | CONCLUSION

In this letter, we presented AWL a new low-cost localization algorithm for mobile wireless networks. The proposed algorithm uses both neighbouring anchor and normal nodes location information and hence does not require an increased anchor density. It besides weights the collected location information by aggregating different metrics of different types providing hence a good robustness against the uncertainty of certain metrics. We considered three simulation scenarios in order to evaluate the performance of AWL. Simulation results showed that AWL outperforms the other state of the art techniques under all the considered scenarios. In our simulations, we used fixed values for the different parameters of our algorithm. However, some tradeoffs need to be deeply analyzed in order to determine the appropriate optimal setting of these parameters. For



(a) $v = 1m/s$ (b) $v = 5m/s$ (c) Heterogeneous network

FIGURE 1 Localization accuracy under different number of anchors

instance, decreasing the broadcast period T_a would generally improve the algorithm accuracy but on the cost of higher communication overhead. There is nevertheless an optimal point after which decreasing T_a will not have a positive effect on the accuracy of the algorithm. Values lower than the optimal value unnecessarily increase the communication cost. Currently, we are performing a comprehensive study evaluating the performance of our algorithm under various values and combinations of its parameters. This study will enable us to draw practical guidelines on how to set these parameters in order to reach the best performance of the algorithm.

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