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Research paper

Enabling accurate range free localization for mobile sensor networks

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Abstract

The Existing localization algorithm was Sequential Monte Carlo (SMC) method for mobile sensor networks. In this paper, we propose an energy efficient algorithm called novel localization, which can achieve high localization in a better way. In existing algorithm, high Localization is achieved by getting more number of beacon nodes as input which improves the computational cost and decreases the sampling efficiency to a higher rate. But in the Proposed algorithm, we achieve high Localization accuracy with less number of beacon nodes itself thus the computational cost will be less and the sampling efficiency will be high. Our algorithm uses the approximate calculated position information of sensor nodes to increase the localization accuracy. The existing algorithms doesn't have high localization accuracy when nodes move very fast, so we have propose a new algorithm, novel localization which is executed based on spped of nodes. The novel algorithm improves the Localization accuracy also when the node move fast.

Keywords: *Sensor, Localization, NOVEL algorithm, VMSL.*

1. Introduction

Wireless and sensor networks (WSNs) have been used in many fields, including environmental and habitat monitoring, precision agriculture, animal tracking, and disaster rescue. In many applications, it is essential for nodes to know their positions. For example, data should be labeled with the positions where they are collected to help the scientists perform corresponding analysis. Position information of nodes are also necessary in many network protocols, , e.g., clustering and routing which depend on the geographical information of nodes [1].For example, geographical routing protocols such as Greedy Perimeter Stateless next-hop relaying node. The procedure through which the nodes obtain their positions is called localization. Localization, which are aware of their positions and sensor nodes which need to determine their positions using a localization algorithm. A straightforward method for localization in WSNs is to use existing localization techniques, e.g., attaching a Global Positioning System (GPS) receiver on every sensor node. However, as the scale of sensor networks becomes larger and larger, these methods become infeasible because of their high cost or inconvenience. Many localization algorithms have been proposed in the past several years. Depending on whether absolute range measurements (point-to-point distances, angles, etc.) are used or not, they can be roughly classified into two categories range based and range-free. Range-based algorithms[1]usually need some special hardware to obtain accurate absolute range measurements and can achieve higher localization accuracy than range-free algorithms. Range-free algorithms, on the other hand, do not need special hardware and are low costly and more attractive in recent years. In some recently emerging applications such as animal monitoring and tracking sensor nodes may move after deployment. These nodes form mobile sensor networks in contrast to traditional static sensor networks in which sensor nodes remain stationary after deployment. The motion of sensor nodes makes most existing localization algorithms designed for static sensor networks inapplicable to mobile sensor networks. The simple idea of executing these algorithms periodically in a mobile sensor network is infeasible, because this will incur high communication cost and/or high computational cost . There are some localization algorithms specially designed for mobile sensor networks. All of them are based on the Sequential Monte Carlo[4] (This is because the posterior distribution of a sensor node's position after move can be naturally formalized using a nonlinear discrete time model and the SMC[2] method provides simulation-based approaches to estimating the distribution. Previous SMC - based localization[2] algorithms either suffer from low sampling efficiency or require high beacon density to achieve high localization accuracy. In such localization algorithms, a sensor node's position distribution is represented with a set of weighted samples. In order to obtain enough valid samples to Accurately characterize the distribution of its position, a sensor node needs to repeat the sampling step (generate candidate samples) and the filtering step (evaluate candidate samples and filter out invalid samples) many times. However, generating candidate samples is for the usually a very costly operation. For example, we will show that, on the Micaz platform the cost of generating a candidate sample is much higher than evaluating it. Because sensor nodes usually have limited computational ability, it is necessary to improve the sampling efficiency in order to reduce the computational cost. Another problem of most existing SMC-based localization algorithms is that they only rely on increasing beacon density to improve localization accuracy. However, beacon nodes are usually more expensive than sensor nodes. Because there are much more sensor nodes than beacon nodes in a sensor network, it will be very beneficial if sensor nodes can be used to improve the localization accuracy. In this paper, we propose an energy efficient algorithm which addresses both aforementioned issues. The algorithm is based on the sequential Monte Carlo Localization (MCL) algorithm proposed and is named Weighted MCL[4] (NOVEL). NOVEL archives high sampling efficiency and achieves high localization accuracy even when the beacon density is based on the NOVEL algorithm and low. However, NOVEL[5] incurs much more communication cost than the original MCL[4] algorithm. In order to reduce the communication cost, we propose two approximate algorithms, NOVEL-A and NOVEL-B which can achieve nearly the same localization accuracy as NOVEL but incur much less communication cost. In fact, compared with MCL, NOVEL-A, and NOVEL-B incur only slightly additional communication cost (tens of bytes) but achieve much higher localization accuracy with much less computational cost. NOVEL uses the following techniques to improve the sampling efficiency and localization accuracy. In existing algorithms, a technique called bounding-box is used to improve the sampling efficiency by reducing the scope of the selecting of candidate samples. By using two-Hop beacon neighbors' negative effects and sensor neighbors' estimated position information, NOVEL further reduces the average size of the sensor nodes' bounding-boxes by a factor of up to 87 percent and, consequently, improves the sampling efficiency by a factor of up to 95 percent. By using estimated position information of sensor nodes, NOVEL greatly improves the localization accuracy. Compared with MSL which uses similar method, NOVEL achieves similar localization accuracy but is much more efficient in terms of both communication cost and computational cost. Further more, it can be used in static sensor networks without the need of experimentally tuning parameters as in algorithms such as MSL*[4]. Taking advantage of this property, we propose a new algorithm in which NOVEL is iteratively executed with different assumptions on the nodes' speed. The new algorithm can dramatically improve localization accuracy. We have evaluated the performance of the proposed algorithms both theoretically and through extensive simulations. We have validated the convergence of the proposed algorithms in real environments by implementing it in a real deployed sensor network. We also have implemented some other SMC[2]-based localization algorithms and compared their performance with our proposed algorithms. The results show that, even in static sensor networks, our proposed algorithms can effectively improve the localization accuracy without the need of any additional. Parameters. So our proposed algorithm is sufficient both for the mobile sensor networks and also for the wireless sensor networks and the proposed algorithm gives both the high sampling efficiency and the high Localization accuracy with less amount of computational cost and also with the less amount of communicational cost.

2. Existing System

The Existing algorithm consists of three steps. initialization, importance sampling, and filtering. In the initialization step, N samples are randomly drawn from the deployment area. In time unit t, in the importance sampling step, candidate samples are drown based on the samples in the previous time unit and their weights are computed using the observations collected in time unit. In the filtering step, samples with weight 0 are filtered out. The importance sampling step and the filtering step may repeat several times in order to obtain enough number of candidate samples with weight greater than 0. Then N samples are selected from these candidate samples and their weights are normalized. At last, the weighted average of the N samples is used as the estimation of a sensor node's position in the current unit time. In some recently emerging applications such as animal monitoring and tracking sensor nodes may move after deployment. These nodes form mobile sensor networks in contrast to traditional static sensor networks in which sensor nodes remain stationary after deployment. The motion of sensor nodes makes most existing localization algorithms designed for static sensor networks inapplicable to mobile sensor networks. The simple idea of executing these algorithms periodically in a mobile sensor network is infeasible, because this will incur high communication cost and high computational cost..

3. The Proposed System

In this section, we describe our Proposed NOVEL algorithm in detail. We first introduce the network model, then describe the three main parts of NOVEL: bounding-box construction, samples' weights computing, and maximum possible localization error computing.

The NOVEL algorithm follows the generic framework presented in Algorithm 1 and makes the following modifications. Before starting sampling each sensor node constructs a bounding-box from which the candidate samples are drawn For each candidate sample, its weight is computed with our proposed weight computing methods .Finally, before broadcasting the estimated position information to other sensor nodes, each sensor node computes its maximum possible localization error with our proposed maximum possible localization error computing method The iterative NOVEL (INOVEL)[5], which can dramatically improve the localization accuracy when nodes move very fast, is described at the last of this section. There are three modules that are 1.Bounding box construction, 2. Weighting samples, 3.Calculating the approximate error approximation.

3.1. Building the Bounding-Box:

There are two areas involved in MCL: the candidate samples area and the valid samples area. The candidate samples area is used to draw new candidate samples and the valid samples area is used to filter out invalid samples. When the candidate samples area is large and the valid samples area is small, candidate samples drawn in the sampling step have high probability to be filtered out in the filtering step. In MCL, the possible locations of a sensor node after move lie in a disk with radius vmax. So the size of the candidate samples area will increase when vmax increases. On the other hand, when sd increases, the size of the valid samples areas will decrease. Denote by Vt the total number of candidate samples drawn in the sampling step in time unit t and define the sampling efficiency.

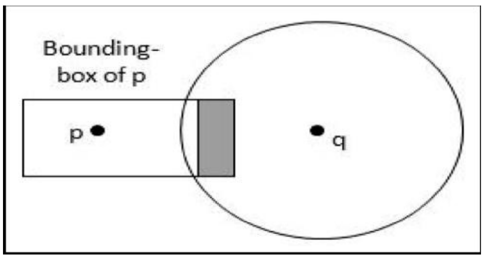

Fig 1. Weighting the Samples

Weighting the Samples

The first method needs to know the whole set of samples of all the sensor neighbors, which incurs high communication cost. As illustrated, if we know s's bounding box We explain this as follows: As illustrated vmax can impact the "quality" of the generated candidate samples in the sampling step. In the two figures, the disk denoted by I represents the whole valid samples area of a sensor node in last time unit, and the ellipse denoted by II represents the valid samples area covered by the sensor node's sample set in last time unit. Pt_1 and Pt are the real positions of the sensor node in last time unit and in current time unit, respectively. We can see that when vmax is small, only a small part of the valid samples area in current time unit can be covered by the candidate samples area. Because all the valid samples are drawn from this part, the position estimation of a sensor node will be inaccurate. When vmax is large, the candidate samples area are larger than def can cover a larger part of the valid samples.

3.2. Computing Error Approximation:

After obtaining N valid samples, a sensor node computes the weighted average of these samples as its position estimation. Using the position estimation and the bounding box, a sensor node can compute its ERx and ERy, [3]as illustrated. Do the same to xmax, ymin and ymax we can get reducedERx andERy. A more riskily method is to use the smallest rectangle enclosing all of p's valid samples to compute ERx and ERy. This method can improve localization accuracy a lot. However, when using this method the procedure of constructing the bounding-box should be carefully manipulated. In this case the inequality presented in may not hold and some inconsistence may happen. For example, it is possible that xmin is larger than xmax and consequently the bounding-box cannot be built. After p gets, it broadcasts them to its neighbors. Its neighbors will use these information to compute their position estimation in the next time unit. So when vmax increases, the localization accuracy can be improved. However, after vmax exceeds a threshold, the candidate samples area can cover the whole valid samples area and the localization accuracy should not be affected by vmax any more.

3.3. Iterative Novel Localization

The localization accuracy of NOVEL will degrade when vmax increases. This is because when vmax increases, the constraints introduced by sensor nodes' estimated position information become very weak and cannot be used to improve the localization accuracy effectively. In NOVEL the candidate samples are directly drawn from the bounding-box so it is also applicable even when vmax ¼ 0. Here, we propose INOVEL[5], the Iterative NOVEL, which can alleviate the negative effects of vmax on NOVEL's localization accuracy. The idea is simple: After all sensor nodes obtain their position estimation in time unit t, they broadcast their position estimations to their neighbors. Upon receiving the new position estimations, the NOVEL is executed with the assumption that vmax equals to 0.

3.4. Performance Evaluation through simulation:

We evaluate the performance of the proposed algorithms through extensive simulations. We modify the widely used simulator developed to implement the proposed algorithms. In order to evaluate our contributions in improving sampling efficiency, we also implement the MCL algorithm and the MCB[6] algorithm and compare their sampling efficiency with our algorithms. In order to evaluate our contribution in improving localization accuracy, we compare our methods with the methods proposed in MSL. Because MSL and MSL use different resampling strategy from that of MCL, for consistency in comparison, here we implement variants of MSL and MSL with the same resampling strategy as in MCL and call them VMSL and VMSL[7], respectively. The communication cost of VMSL and VMSL are the same as that of MSL and MSL. We consider the following metrics: 1) localization accuracy, 2) computational cost, and 3) communication cost. The main parameters we consider are nodes' maximum speed vmax, node degree nd, and beacon degree sd, for they are the main factors affecting the algorithms' performance. When considering the impact of communication irregularity on the algorithms' performance we use the. We tune the value of d in the model to simulate different irregularity of communications. We assume that all the nodes are uniformly deployed in a square region and the communication range r is set to be units. We use a modified Random Waypoint mobility model proposed in the MCL[4] algorithm.

3.5. Localization accuracy:

Localization accuracy is the most important metric in evaluating localization algorithms. we study how the localization accuracy of different algorithms varies when sd, nd, and vmax varies shows how the localization accuracy of different algorithms varies when sd increases. When sd increases, in all algorithms the localization accuracy improves. However and our proposed algorithms perform much better than other algorithms. This is because VMSL*[7]and our proposed algorithms use sensor nodes' estimated position information to improve localization. We can also see that NOVEL-A and NOVEL-B achieve nearly the same localization accuracy as NOVEL shows how the localization accuracy varies when nd increases. We can see that the localization accuracy of and our proposed algorithms improve when nd increases. We can also see that, when the accuracy of MCL and MCB[6] is also improved slightly when nd increases. The reason is as follows: When nd is small, the network is very sparse and maybe some beacon nodes within of a sensor node cannot be found as two-Hop beacon neighbours. When almost all the beacon nodes within 2r of a sensor node can be found and the increase in nd will not affect the localization accuracy.

4. Conclusion

In this paper, we present an accurate and energy efficient range-free localization algorithm for mobile sensor networks. We measured the cost of key operations in SMC based localization algorithms on real hardware and found that a high sampling efficiency is necessary to reduce the computational cost. Then, we propose a set of algorithms which achieve high sampling efficiency and high localization accuracy. The results from our simulations and algorithms on the improvement of localization accuracy and reduction of energy consumption. In our simulations, we find that irregular communications will not only degrade the localization accuracy of the proposed algorithms but also will incur much more computational cost. In our implementation of the proposed algorithms in real environment, we find it is difficult to determine a maximum transmission range between two nodes. The connectivity between two sensor nodes is very unstable. The connectivity status may vary greatly in different times, in different places, or even between different sensor nodes. In this case, the performance in real implementation will be much worse than the performance obtained from simulation

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