Enabling Energy-Efficient and Quality Localization Services

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Abstract

Recent localization research has focused on improving the accuracy of pinpointing the physical location of a target. We think that the ***energy efficiency*** *and the* ***quality of the localization services (QoLS)*** *are equally important properties of localization systems. We refer to the QoLS as the timely supply of the location information to the applications. Energy efficiency and quality are seemingly two contradictive goals in terms of determining the rate of triggering the localization systems to perform the necessary computation and communication. In that, a lower location sampling rate contributes to a lower level of energy consumption but in the meantime compromises the timeliness of acquiring the location information. Opting for energy efficient and quality localization services, we propose a* ***mobility-aware mechanism*** *that adapts the sampling rate to the target mobility. Results from our simulations confirm that the adaptive sampling approach is promising and effective.*

1. Introduction

Location-aware applications [1] are coming of age and to be realized in many everyday scenarios, for instance, asset tracking in warehouses, patient monitoring in medical facilities, and household management at home. These applications provide different types or levels of services based on the location information, supplied by *localization systems*. Much recent localization research [2][3] [4] concentrates on improving the accuracy of pinpointing the physical location of the target. We think, however, that the *energy efficiency* and the *quality of localization service (QoLS)* are two issues equally important to address.

Energy efficiency of the *mobile units (e.g., tags or badges)* attached to the tracked target is essential for any practical deployment. That is, a highly accurate location system is still of little use if it requires frequent recharging of the mobile units. In the context of localization system, the energy consumption of a mobile unit is proportional to the *sampling rate* of the location information – the rate at which the localization infrastructure and its counterpart mobile units are triggered to perform the necessary communication and computation.

The sampling rate of the location information may also impact the quality of localization service. Consider two consecutive samples. There is a short period of time that the application does not have the most up-to-date location of the target. Hence, even when the location information provided by the localization system is perfect, the application might not be able to detect whether the target enters a *critical region* such that the application can activate the corresponding services in real time. Many location-aware applications, for example, enemy tanks crossing the border line, expensive jewelries exiting the shop, young children entering the balcony, or sales leaving the office without the mobile phones, do require timely detection of the target entering certain critical areas or boundaries. We refer to the *timely supply of the location information* as the quality of the localization service.

The dilemma with *fixed-rate sampling* is that the sampling rate can be set high to provide real-time location information, but when the target is far from the critical region where the timely service requirement is not as high, the high sampling rate will be unnecessary and there is no need for such waste of energy. Aiming at improving the energy efficiency and quality of the localization service at the same time, we propose an *adaptive location information sampling mechanism* based on the location and *predicted mobility* of the target. Given the critical region to watch closely from the application, the mechanism controls the rate the localization system is triggered to acquire location information. When the target moves fast or close to the critical region, the sampling rate increases to enable timely detection of target entering the critical region at the application level. When the target slows down or moves away from the critical region, the sampling rate decreases to conserve energy. This *mobility-aware adaptive sampling mechanism* can be coupled tightly with any localization systems and the integrated mobility-aware localization systems can work transparently for location-aware applications with quality of location service requirement.

The idea of using predicted mobility for overhead optimization has appeared in the literature of mobile networking computing. For object tracking sensor networks, predicted object mobility is used to activate sensor nodes that are falling into the mobile object's proximity while the other nodes hibernate to conserve energy [5]. Limiting the region of communication or sensing, as proposed in the literature, reduces the system overhead in the spatial dimension. The mobility-aware adaptive sampling mechanism, complementary to the prior work, exploits the temporal dimension.

Our contribution is two-fold. First of all, we propose a mobility-aware adaptive sampling enhancement to general localization systems. Secondly, with simulations, we validate that the mechanism is able to provide both energy-efficient and quality localization services to location-aware applications.

2. Mobility-Aware Sampling Mechanism

The idea of mobility-aware adaptive sampling is applicable for general localization systems. To focus more on evaluating the adaptive sampling mechanism, we consider a simplified mechanism for 1-dimensional space. In this section, we will first describe the mechanism for general localization systems, and then detail the simplified mechanism for the proof-of-concept evaluation.

2.1. General Mechanism

The objective of the mobility-aware adaptive sampling mechanism is to sample right on the time the target comes to the critical point as illustrated in Figure 1(a). *P1* and *P2* are the two most recent sample points. The velocity is estimated by dividing the vector *P1* to *P2* to the time between the two points. The critical point *C* is where the line of movement intersects with the critical region. As the target arrives at position *P2*, the system sets the time for the next sample by calculating the time for the target to move from the current position *P2* to the critical point *C* in velocity *V*.

To avoid drastic error due to very rough estimation of velocity, we further bound the maximum value of the sampling interval. This upper bound ensures that the system captures the movement change within a certain time interval. On the other hand, since an excessively short sampling interval may result in extensive use of energy, we also set the lower bound to avoid such ineffective use of energy. Both the upper and lower bounds can be system parameters specified by the applications for different quality or energy efficiency requirements.

2.2. Simplified Mechanism

In the simplified mechanism, the problem is reduced to a 1-dimensional space. Illustrated in Figure 1(b), regions more than *R* distance away from the reference point are set as the critical region. The critical points thus fall on a circle centered at the reference point. In a 1-dimensional space, only the distance instead of the coordinate is available. We assume a beacon node is placed at the reference point. Using any ranging technology, we can obtain the distance between the target and the beacon node. The goal of this mechanism is to reduce the amount of radio message exchange performing distance estimation.

To keep track of the target position, the beacon repeatedly sends probing messages to trigger the target to send back a reply message. During the message exchange, both nodes will be able to know the relative distance by performing ranging. The target could use the two most recently sampled distances to estimate the outgoing relative velocity vector V with Equation (1).

$$V = (d_2 - d_1)/(t_2 - t_1) \tag{1}$$

After knowing the relative velocity, the time interval to send the next probing message T can be properly tuned by Equation (2), which is the expected time elapsed for the target to move across the critical points.

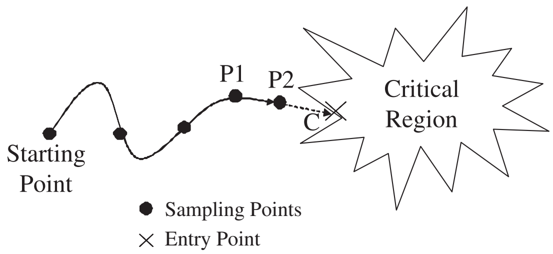
$$T = |(R - d_2)|/|V| \tag{2}$$

We take absolute value on $R - d_2$ to ensure that the frequency is set high when the distance is close to the critical region. Also, no matter whether the target is approaching to or moving away from the reference point in this circular area, the probing frequency goes high when the relative velocity increases. Similar to the general mechanism, the sampling interval is limited by a lower bound and an upper bound.

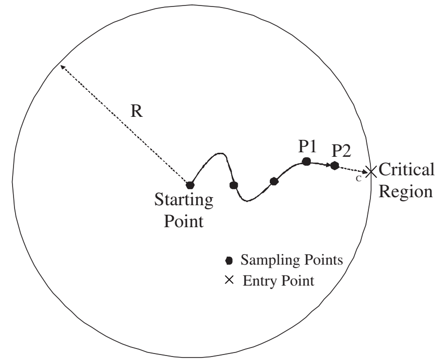
The derived sampling interval T is then sent back to the beacon node along with the reply message. The beacon node can then schedule the next probing message after time T. Since T is known on both sides, the radio interfaces can be completely turned off for better energy efficiency.

3. Simulation

The objective of the simulation is to demonstrate quantitatively the benefit of mobility-aware adaptive sampling mechanism, in particular, how much the energy efficiency



(a) General mechanism



(b) Simplified mechanism

Figure 1. Illustration of Mobility-Aware Sampling

and the timeliness of the critical point localization can be improved by adapting to the predicted velocity. We implement both the fixed-rate and mobility-aware adaptive sampling mechanisms.

3.1. Methodology

The mobility-aware adaptive sampling mechanism is implemented in the network simulator version 2, i.e., *ns-2* [6]. The reference and target node are simulated by a simple 2-wireless-node scenario. The radio range is set to 20 meters while the area of experiment is set to 15x15 square meters to ensure that the two nodes will be reachable to each other throughout the simulations. The range of the reference point to the critical point R is set to 5 meters.

To simulate the movement of the user, we adopt the random waypoint mobility model [7], which matches the everyday behavior of human migration. In our simulations, the speed of each movement is chosen uniformly random from 0.3 to 2 meters per second, which is also around the speed range of human walking. We vary the pause time interval from 0 to 100 seconds. With different pause time, random moving speeds and destinations are generated to run an 8-hour simulation to cover the 9 to 5 working hours.

3.2. Performance Metrics

The performance metrics are detection accuracy and energy consumption. The application would prefer a timely report when the target just arrives at the critical region. In our simulations, the location of the target is reported when the target is R unit distance away from the reference point. Thus, the detection accuracy is defined as the distance between the reported position and the critical distance R.

For simplicity, we assume that given a localization system, the energy consumption per localization is constant and consider the minimum localization system. In that, a node equipped with an ultrasound and/or RF transceivers is placed at the reference point. The target equipped with the corresponding transceivers receives the ultrasonic and/or RF signals to estimate its range to the reference point from which the target velocity can be estimated and the next sampling time can be derived, using the mechanism defined in the previous section.

Consider the localization systems. Since the ultrasound and RF interfaces are the primary energy consumer, we track the energy consumption by measuring the amount of time that the ultrasound and RF interfaces stay on. The total power consumption can be obtained by multiplying the time intervals with the energy the interface requires to stay on. We use the power consumption profile of the TR1000 radio [8] (Table 1) to approximate the power usage of the RF and ultrasound interfaces in the minimum localization system. Note that when the ultrasound or RF interface stays in the idle listen mode, the power consumption is close to the transmit and receive mode.

Modes	Power consumption
Transmit	14.88 mW
Receive	12.5 mW
Idle	12.36 mW
Sleep	0.016 mW

Table 1. TR1000 Radio Power Consumption

3.3. Results Without Localization Error

The simulation results with zero localization error is shown in Figure 2. In the figure, the x-axis is the radio energy consumption and the y-axis is the detection accuracy. Because no error comes from the localization system, the error observed here is entirely due to untimely sampling.

The fixed-rate sampling results are drawn by simulations that each uses a different sampling interval. The 6 data points in the plot are results of sampling interval being 0.1, 0.5, 1.0, 1.5, 2.0, and 2.5 seconds respectively. The curve shows that there exists a trade-off between the error and energy efficiency. The higher the accuracy requirement from the application, the more energy the system will consume.

The fixed-rate result also acts as a performance bound. Any effective mechanisms must produce error-energy curves that are to the lower left of the fixed-rate curve. These curves suggest that these effective mechanisms can achieve better accuracy given the same energy use in the fixed-rate sampling, and better energy efficiency for the same accuracy.

The other two lines show the results of tuning the upper and lower bound of the mobility-aware sampling mechanism described in the mechanism section. We first fix the lower bound to 0.1 seconds and the upper bound to 0.1 seconds. Then, we gradually relax the upper bound from 0.1 to 4.5 seconds (0.1, 0.5, 1.0, 1.5, 2.5, 3.5, 4.5). This gives the upper bound line. We then fix the lower bound to 2.5 and the upper bound to 2.5 seconds. To obtain the effect of relaxing the lower bound, we decrease the lower bound from 2.5 to 0.05 seconds (2.5, 2.0, 1.5, 1.0, 0.5, 0.1, 0.05). We observe from the upper bound results, the energy consumption drops rapidly at the beginning while the average error does not vary a lot. This shows that the mobility-aware mechanism effectively adjusts the sampling interval to a slower rate to conserve energy and yet maintains a similar level of accuracy. After the initial drop, further relaxing the upper bound does not help too much in reducing the energy consumption while the error increases significantly. This means that when the sampling interval upper bound is too large, the system becomes less sensitive on accurately predicting the target movement. In the lower bound set of results, the average error decreases as the lower bound decreases. The error stays around 40 cm even if the lower bound is relaxed further down to 0.05 seconds. We think the reason that the error cannot be further decreased is due to the accuracy of the velocity prediction, i.e., the choice of upper bound. With an upper bound of 2.5 seconds, the system's responsiveness is bounded.

By the above thorough exploration of the parameter space, we have found that the performance of the mobility-aware sampling mechanism, falls in the lower left area of the fixed-rate sampling results. This indicates that the mobility-aware mechanism can improve both the accuracy and energy efficiency of the localization service.

4. Conclusion

In this work, we propose and validate a mobility-aware adaptive sampling mechanism that meets the accuracy requirements of applications and, in the meantime, significantly reduces energy consumption for the underlying localization systems.

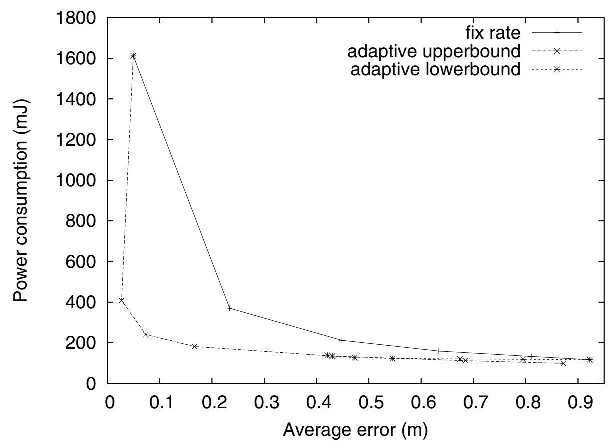


Figure 2. Results Without Localization Error

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