Arab Gulf Journal of Scientific Research, 27 (1&2): 48- 58 (2009)

Research Paper Ref. No 2490

A Hybrid Localization Protocol for Mobile Sensor Networks

بروتوكول مهجن لتحديد المواقع بواسطة شبكات الاستشعار اللاسلكية

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Abstract: Many localization techniques and protocols have been proposed for wireless sensor networks. However, few of these techniques consider the mobility of the networked sensors. When sensors are mobile, localization must be invoked periodically to enable sensors to track their location. Localizing should be made frequently to allow the sensors to track their location accurately. However, localizing frequently is expensive in terms of energy consumption and program time. This research proposes an efficient Hybrid Localization Protocol (HLP) for mobile sensor networks that dynamically invokes adaptive and predictive protocols based on some heuristics. The proposed HLP determines the optimal localization frequency based on the sensor's speed and mobility pattern predictability. Optimal localization frequency reduces the energy consumption of localization while increasing the localization accuracy. Experimental simulation results and analysis show that the proposed protocol is more efficient in terms of energy consumption and localization accuracy than the existing counterpart protocols.
Keywords: *Wireless sensor networks, mobile networks, sensor localization techniques, predictive localization protocol, adaptive localization protocols.*

المستخلص: كثير من تقنيات تحديد المواقع والبروتوكولات تم اقتراحها، ومع ذلك فأن قليلا من هذه التقنيات تأخذ بعين الأعتبار تنقل المجسات الشبكية. عندما تكون المجسات متنقلة فإن عملية تحديد المواقع يجب أن يتم استدعاؤها دوريا لتمكين المجسات من تتبع المواقع. أن تحديد المواقع يجب أن يتم تكرارا في فترات قصيرة للسماح للمجسات بتتبع المواقع بطريقة دقيقة. ومع ذلك فإن تحديد المواقع تكرارا في فترات قصيرة مكلف من حيث استهلاك الطاقة وزمن تنفيذ البرنامج. هذا البحث يقترح بروتوكولا مهجنا لتحديد المواقع بواسطة شبكات الاستشعار اللاسلكية يقوم بأستدعاء البروتوكولات التواؤمية والتنبؤية بطريقة ديناميكية بناءاً على معايير استدلالية. البروتوكول المهجن المقترح لتحديد المواقع يعين التردد الأمثل لتحديد المواقع بناء على سرعة المجسات والقدرة على تنبؤ نمط التنقل للأجسام المراد تحديد مواقعها. التردد الأمثل لتحديد المواقع يقلل من استهلاك الطاقة لعملية تحديد المواقع في الوقت الذي يزيد من دقة عملية تحديد المواقع. أن نتائج تجارب المحاكاة والتحليلات التي تم تنفيذها أظهرت أن البروتوكول المقترح أكثر فعالية من حيث استهلاك الطاقة ودقة عملية تحديد المواقع مقارنة بالبروتوكولات الحالية المناظرة.
كلمات مدخلية: *شبكات الاستشعار اللاسلكية، شبكات المحمول، تقنيات تحديد المواقع بواسطة المجسات، بروتوكول تحديد المواقع التنبؤي، بروتوكولات تحديد المواقع التواؤمية.*

INTRODUCTION

Advances in technology have made it possible to build ad hoc sensor networks using inexpensive nodes. Each node consists of a low power processor, a modest amount of memory, a wireless network transceiver and a sensor board. A typical node is comparable in size to 2 AA batteries (Hill, *et al.* 2000). Wireless Sensor Networks can be employed in applications ranging from environmental monitoring and battlefield surveillance to condition based maintenance (Estrin, *et al.* 2002; Li, *et al.* 2002; Estrin, *et al.* 2001).

The localization problem is defined as estimating the position or spatial coordinates of wireless sensor nodes (Ramadurai and Sichitiu, 2003). Localization is the ability of a sensor to find out its physical coordinates. This is a fundamental ability for embedded networks because interpreting the data collected from the network will not be possible unless the physical context of the reporting sensors is known. In addition, localization is important in Mobile Ad hoc NETworks (MANETs) where several protocols utilize geographical information to improve operation (e.g., Ko and Vaidya, 1998). Existing research has focused on addressing the localization problem for static sensor networks (sensors once deployed are stationary throughout life-time) (Juang, *et al.* 2002). Numerous localization techniques for wireless sensor networks have recently been proposed. Many techniques calculate the position of nodes based on the information of a set of anchor nodes that know the locations. The methods typically assume static network topologies. However, many sensor network applications demand the consideration of mobile sensor nodes.

No universally acceptable solution has been adopted for realistic, outdoor environments, despite the attention the localization problem in WSN have received (Stoleru, *et al.* 2007). Localization may be carried out in one of several ways. If the node is equipped with a Global Positioning System (GPS) card, it can determine its coordinates by receiving signals from a number of satellites. Differential GPS requires that the node also receives signals from nearby ground reference stations. Alternative localization approaches have been proposed to allow nodes to learn their location either from neighboring nodes or from reference beacons (Bulusu, *et al.* 2001; Bulusu, *et al.* 2000).

Localization techniques are divided into two categories: centralized localization techniques and distributed localization techniques. Centralized techniques require central computation that would be infeasible for mobile applications because of the high communication costs and inherent delay. Distributed localization techniques rely on each node determining its location with only limited communication with nearby nodes. Distributed localization techniques are classified as range-based techniques and range-free techniques. Range-based techniques use distance estimates or angle estimates in location calculations, while range-free techniques depend only on the contents of received messages. Range-free localization algorithms are a cost effective alternative to the more expensive range-based approaches (He, *et al.* 2003). There are two main types of range-free localization algorithms that have been proposed for sensor networks: local techniques that rely on a high density of seeds so that every node can hear several seeds, and hop counting techniques that rely on flooding a network (Hu and Evans, 2004).

Several applications utilize mobile sensors. For such applications, dynamic management of localization is necessary to maintain energy efficient operation (Juang, *et al.* 2002). There are two classes of dynamic localization approaches: Adaptive approach and predictive approach. Adaptive approach dynamically adjusts the localization period based on the recent observed motion of the sensor. In this approach, localization frequency is proportional to the sensor's speed. Predictive approach lets the sensors estimate their motion pattern and use this pattern to project their location in the future, without explicit localizing. If the prediction is accurate, which occurs when nodes are moving predictably, estimates of location may be generated without localization, allowing for farther reduction of the localization period (Tilak, *et al.* 2005).

The dynamic localization technique in mobile sensor networks is the technique that sensors use to calculate their location dynamically and periodically. Three dynamic localization techniques are proposed in the literature: static localization technique, adaptive localization technique and predictive localization technique. Static localization technique is a trivial technique where the localization period is fixed. An example protocol that uses this technique is the Static Fixed Rate protocol (SFR). The main advantage of SFR is its simplicity, while its main drawback is the low accuracy of localization. In adaptive localization technique the localization period is changed adaptively depending on the motion of the sensor node. An example protocol that uses this technique is the Dynamic Velocity Monotonic (DVM). As the sensor's speed increases, the localization frequency increases to reduce the localization error and vice versa. In predictive localization technique the sensor nodes predict their location based on their previous motion. To predict the motion, the nodes use dead reckoning. An example protocol that uses this technique is the Mobility Aware Dead Reckoning Driven (MADRD). Depending on how well the mobility of the sensor is predicted, the localization frequency can be significantly reduced using this approach. The intuition is that the mobility pattern is changing, and more localization is needed to capture the new mobility pattern as well as to limit the localization error. However, if the prediction is accurate, the confidence in the predictor increases and the localization period is increased. A state diagram for MADRD is shown in Figure (1). In this figure, HC refers to the high confidence state where the predictor is scoring well and localization period is increased. LC refers to the low confidence state where the predictor is not scoring well and the period is decreased. Erroneous predictions move the predictor towards the LC, while correct predictions move it towards HC. States S1 and S2 provide some level between LC and HC (Tilak, *et al*. 2005). The location error is measured at any time point by the distance difference between the actual location of the node and the computed location. Figure (2) shows the location error at different time points.

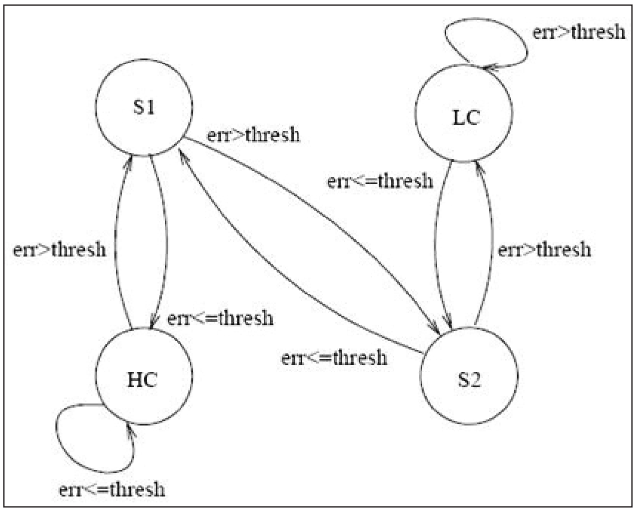

Fig. 1. State diagram of MADRD protocol.

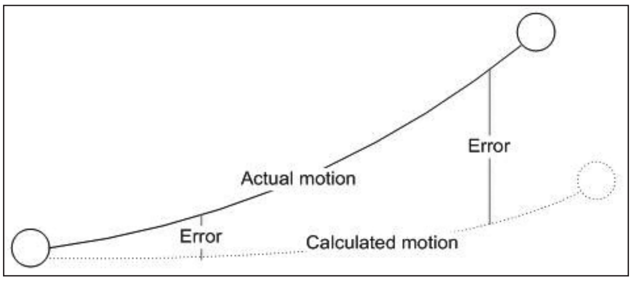

Fig. 2. Location error.

This research proposes an efficient Hybrid Localization Protocol (HLP) for mobile sensor networks. The protocol combines both adaptive and predictive protocols. These two protocols are dynamically invoked based on some heuristics. The invoked protocol and optimal localization frequency at any localization point are determined by both the sensor's speed and predictability of the sensor's mobility pattern. The optimal time period of localization reduces the energy consumption of the sensor and increases the localization accuracy. HLP combines the advantages of both the adaptive and the predictive approaches. The approach trades-off between energy consumption (through reducing frequency of the localization process) and localization accuracy (through increasing frequency of the localization process). HLP is generic since it does not assume any specific adaptive or predictive localization protocol. It assumes that these two protocols are given when HLP executes.

RELATED WORK

The Princeton ZebraNet project (Juang, *et al*. 2002) is a good example of a mobile sensor network application that explores wireless protocols and position-aware computation from a power-efficient perspective. One of the project's fundamental requirements is to find the nodes' location on mobile objects. If the project adopts a localization technique for the mobile sensors, they could reduce much of the cost for the system (Yi, *et al*. 2007). Doherty, *et al*. (2001) proposed a centralized technique using convex optimization to estimate positions based only on connectivity constraints given some nodes with known positions. MDS-MAP (Shang, *et al*. 2003) improves on these results by using a multidimensional scaling approach, but still requires centralized computation. Requiring central computation would be infeasible for mobile applications because of the high communication costs and inherent delay; hence distributed localization techniques appeared (Hu and Evans, 2004).

Range-based approaches have exploited time of arrival (Wellenhoff, *et al*. 1997), received signal strength (Bachrach and Taylor, 2005; Patwari and Hero, 2003), time difference of arrival of two different signals (TDOA) (Savvides, *et al*. 2001), and angle of arrival (AOA) (Niculescu and Nath, 2003). Though they can reach fine resolution, either the required hardware is expensive (ultrasound device for TDOA, antenna arrays for AOA), or the results depend on other unrealistic assumptions about signal propagation (for example, the actual received signal strengths of radio signals can vary when the surrounding environment changes) (Hu and Evans, 2004). Furthermore, the TDOA techniques require a high demand on the accurate measurement or estimation of time delay (Sheng and Hu, 2003). In the Centroid method (Bulusu, *et al*. 2000), each node estimates its location by calculating the center of the locations of all seeds it hears. If seeds are well positioned, location error can be reduced (Bulusu, *et al*. 2001), but this is not possible in ad hoc deployments. The APIT method (He, *et al*. 2003) isolates the environment into triangular regions between beaconing nodes, and uses a grid algorithm to calculate the maximum area in which a node will likely reside.

To provide localization in networks where seed density is low, hop-counting techniques propagate location announcements throughout the network. DV-HOP (Niculescu and Nath, 2003) uses a technique based on distance vector routing. Each node maintains a counter denoting the minimum number of hops to each seed, and updates that counter based on messages received. Seed location announcements propagate through the network. When a node receives a new seed announcement, if its hop count is lower than the stored hop count for that seed, the recipient updates its hop count to the new value and retransmits the announcement with an incremented hop count value. The Amorphous localization algorithm (Nagpal, *et al*. 2003) uses a similar approach. The coordinates of seeds are flooded throughout the network so each node can maintain a hop-count to that seed. Nodes calculate their position based on the received seed locations and corresponding hop count (Hu and Evans, 2004). Similar to this work Tilak, *et al*. (2005) presents two protocols to solve the localization problem in the mobile sensor networks. These two protocols decide when to invoke the localization technique. The first protocol is the Adaptive protocol and the second is the Predictive protocol.

METHODOLOGY

DVM improves the performance of SFR in the mobility pattern changes environments. DVM uses velocity as the parameter to compute the localization frequency. MADRD predicts the mobility pattern. Our approach combines the advantages of both DVM and MADRD. It uses both the speed and mobility pattern of the sensors as parameters to determine the localization frequency. Hence, the proposed protocol is a hybrid protocol that combines both DVM and MADRD. The proposed approach is adaptive since it uses either of these protocols adaptively based on the current sensor's state. The sensor's state is specified by the combination of sensor's speed and sensor's mobility pattern. The proposed approach is also dynamic, since it computes the localization frequency dynamically over time. We call the proposed approach Hybrid Localization Protocol (HLP).

Each sensor in the HLP has four states. The sensor's state is defined by the combination of both the sensor's speed and its mobility pattern (whether the sensor moves predictably or not). Table (1) presents these four sensor states and the corresponding localization time period for each state. The localization time period of a state is the time between two localizations. In state 1 the sensor's speed is high and the sensor moves in an unpredictable manner; the localization time period is short because both high speed and mobility unpredictability require short localization time period to maintain acceptable accuracy. In state 2 the sensor's speed is low and the sensor moves in an unpredictable manner; the localization time period is medium because low sensor speed requires long localization period and sensor's mobility unpredictability requires short localization time period to maintain acceptable accuracy. In state 3 the sensor's speed is high and the sensor moves in a predictable manner; the localization time period is medium because high sensor speed requires short localization time period and sensor's mobility predictability requires long localization time period to maintain acceptable accuracy. Finally, in state 4 the sensor's speed is low and the sensor moves in an unpredictable manner; the localization time period is medium because both low sensor speed and sensor's mobility unpredictability require short localization time period to maintain acceptable accuracy. These localization time periods depend on the application requirements and their values for the short, medium, and long localization time periods, are set by the user or programmer.

Table 1. The states of HLP.

State #	Sensor's speed	Sensor's mobility pattern	Localization Time Period
1	High (H)	Unpredictable (U)	Short (S)
2	Low (L)	Unpredictable (U)	Medium (M)
3	High (H)	Predictable (P)	Medium (M)
4	Low (L)	Predictable (P)	Long (L)

At each localization point, HLP measures the sensor's speed and the mobility pattern and then decides the next state and the localization time period accordingly. Figure (3) shows the state diagram of the protocol. HLP transition from one state to another depends on two inputs; the first input is the sensor's speed which takes two values (H for high speed and L for low speed). The second input is the sensor's motion pattern (MP) which takes two values (P for predictable motion and U for unpredictable motion). The output of each state is the localization time period which takes three values (L for long, M for medium, and S for short). Figure (4) lists the pseudo code of HLP. HLP starts by initializing the localization time periods of the four states of the sensors. HLP also sets the threshold error and the threshold speed. These threshold values are application dependent. Usually the threshold error is high in applications that can afford error such as ZebraNet project (Juang, *et al*. 2002).

On the other hand, the threshold error is low in applications that are very sensitive to error such as target detection applications. For the threshold speed, it is low when the application is related to low mobility nodes or semi-static nodes like environmental monitoring. On the other hand, the threshold speed is high when the nodes in the application move in high speed such as battlefield surveillance. The threshold error is used to control the desired accuracy of the protocol and the predictability of the sensor's motion. The threshold speed is used to control the localization time period. HLP is then reset to the initial default state which is state 1. State 1 is selected as the initial state where the localization time period is the shortest. We chose state 1 as the initial state because at first we do not know the mobility pattern which means that it is unpredictable. Since we do not know the speed of the sensor, state 1 represents the safest choice of the initial state. This is because it is not inaccurate if the node is actually moving in low speed at first and we assume it is moving in high speed since the protocol will detect the low speed soon and move to another state. If we assume the opposite, i.e., that the node is moving in low speed while it is actually is moving in high speed then, at first, there will be low accuracy in the prediction because the localization time period will be medium or long based on the sensor's motion predictability pattern.

The initial choice of the states does not have a significant effect on the performance of the protocol. However; state 1 is the safest choice.

After the HLP chooses the initial state, it executes an infinite loop. At the beginning of this loop, HLP assesses the current state (sensor's speed, sensor's mobility pattern) which will determine the optimal localization time period and the next state. This optimal localization time period is an essential advantage of HLP over other protocols. Based on the current sensor's state (sensor's speed, sensor's mobility pattern), HLP determines the appropriate localization protocol (adaptive or predictive) to be used. Hence, HLP exploits the advantages of both adaptive and predictive protocols.

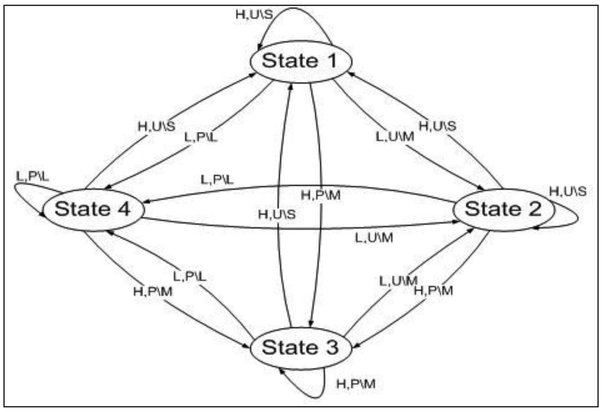

Fig. 3. The state diagram of the HLP.

```
Algorithm HLP (   )
begin
//set state time periods
set state1_T, state2_T, state3_T, state4_T;
set threshold_speed,  threshold_error;
mobility_pattern = Unpredicted;
speed_status = High;
current_state = state1;
state_T = state1_T;
while (1) {
  Localization_Protocol(current_state);
  wait(state_T);
  Speed = (new_location –
             old_location)/State_T;
  if (current_speed > threshold_speed)
    speed_status = High;
  else
    speed_status = Low;
  error = actual_location – calculated_location;
  if (error > threshold_error)
    mobility_pattern = Unpredicted;
  else
    mobility_pattern = Predicted;
  switch(speed_status, mobility_pattern){
    case (High,Unpredicted):
        Current_state = state1;
          state_T = state1_T;break;
    case (Low,Unpredicted):
        Current_state = state2;
          state_T = state2_T break;
    case (High,Predicted):
        Current_state = state3;
          state_T = state3_T break;
    case (Low,Predicted):
        Current_state = state4;
          state_T = state4_T break;
  } // end switch
} // end while
end algorithm
Localization_Protocol(STATE S){
switch (S){
  case state1: call DVM(state1_T); break;
  case state2: call DVM(state2_T); break;
  case state3: call MADRD(state3_T); break;
  case state4: call MADRD(state4_T); break;
 } // end switch
} // end procedure
```

Fig. 4. The pseudo code of HLP.

EXPERIMENTAL RESULTS

In this section we validate the proposed protocol by conducting simulation experiments. The experiments compare the performance of the proposed protocol with some existing localization protocols from the literature. SFR protocol (static localization protocol), DVM protocol (adaptive localization protocol) and MADRD protocol (predictive localization protocol) are used for performance comparison. We developed a Java-based simulation model to simulate HLP protocol and to compare its performance with these protocols. The simulation environment uses a simulation area of 300 by 300 meters and sensor transmission range of 100 meters using IEEE 802.11. The environment uses 36 equally spaced beacon nodes for localization and 24 mobile nodes that carry out the localization. Each simulation experiment was run for 900 seconds. We use a query-based localization mechanism: a node that is interested in localization broadcasts a request – beacons that receive the request reply with their location which can then be used to triangulate the nodes own location. The beacons are placed such that at least three beacons are able to answer each query. Energy is measured in terms of number of localization operations, regardless of the number of primitive operations in the localization process itself.

The sensor's mobility model used in the simulation is the random waypoint model, widely used in the mobile ad hoc network community. In this model, a node picks a random location in the simulated area and starts moving to it with a controllable average velocity. When the node reaches the destination, it pauses for some fixed pause time. The model is predictable while the node is moving, or for the duration of the pause period but not when the sensor pauses or when it starts moving. Furthermore, if the pause time is zero, the model is unpredictable when the node reaches its destination, then picks another location randomly and starts moving towards it. We can control how predictable the model is by manipulating the average speed and the pause time – if the pause times are short, then the sensor has more unpredictable behavior.

The first experiment compares the performance of DVM and HLP in the case of a sensor moving in high constant speed of 20 m/sec. Figure (5) shows the results. Figure (5a) shows the performance of DVM. DVM localizes with high frequency (every 2 sec) since the sensor's speed is high to minimize the localization error. This leads to high energy consumption. In addition, since DVM does not consider the prediction, the error increases linearly until the next localization point. Figure (5b) shows the performance of HLP. Since HLP considers the mobility predictability, the localization period increases (localization frequency decreases) as time elapses since HLP will detect the constant high speed mobility. HLP localizes less often as long as the sensor motion is predicted. This leads to lower energy consumption. In addition, HLP reduces the localization error. This is because HLP lets the sensor update its location, continuously and does not wait until the next localization point to update its location as in DVM protocol.

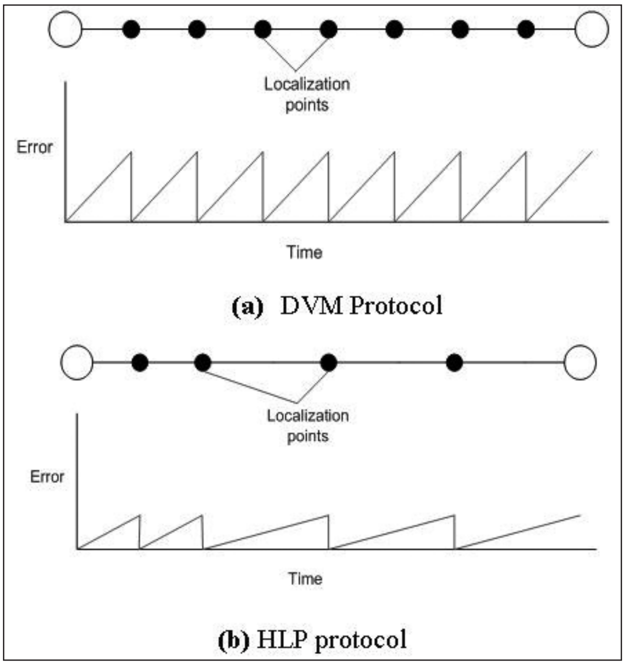

Fig. 5. Localization of a node in high constant motion.

The second experiment compares the performance of MADRD and HLP protocols in the case of a sensor moving in low constant unpredictable speed of 2 m/sec. Figure (6) shows the results. Figure (6a) shows the performance of

MADRD. Since MADRD does not consider the sensor's speed, it decreases the localization time period because the sensor moves unpredictably (low confidence state). However, since the sensor moves in low speed, high localization frequency is not needed. This makes MADRD protocol inefficient in the case of low speed. Although MADRD has high accuracy in this case, it consumes a lot of energy. Figure (6b) shows the performance of HLP. HLP improves performance of MADRD by considering the speed of the sensor. When HLP predicts the motion of the sensor correctly it increases the localization time period. On the other hand, when the sensor moves unpredictably, HLP decreases the localization time period to capture the motion pattern of the sensor. HLP avoids high localization overhead by detecting the low speed motion. HLP can still improve accuracy since the sensor moves with low speed. As Figure (6) shows, localization error of MADRD is worse than that of HLP.

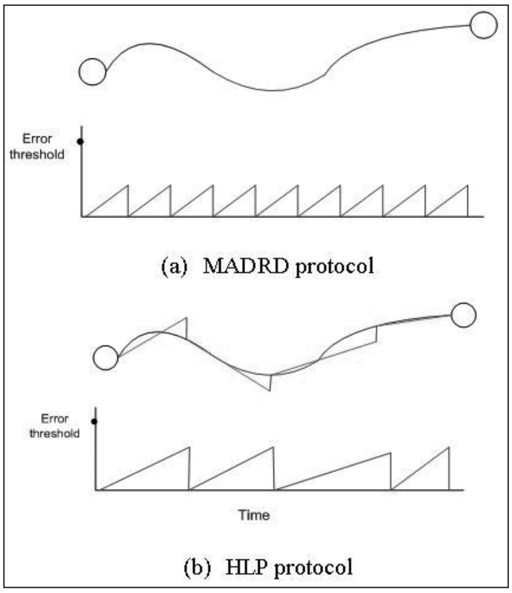

Fig. 6. Localization for a node in unpredictable motion and low speed.

The third experiment compares the effect of varying the pause time on energy consumption (measured by the localization frequency) for SFR, DVM, MADRD and HLP. The sensor's speed is fixed at 1 m/sec. Figure (7) plots the number of localization operations as a function of the pause time. The localization operations are normalized to SFR. The number of localization operations correlates directly with localization energy since the average cost of localization is constant for most localization schemes. In this case of low mobility, the localization frequency of SFR is the highest while that of HLP is the lowest. Hence, HLP has the lowest energy consumption among all the evaluated protocols. For a given protocol there is almost no change in localization frequency as the pause time changes. This is logical for low speed motion. The reason for high localization frequency of SFR is that SFR does localization at fixed periods regardless to the speed of the node. DVM detects the low speed mobility of the node and localizes less frequently. MADRD protocol however localizes even less frequently than DVM. This is because MADRD protocol predicts the mobility pattern of the node. Therefore, there is no need for making a lot of localization since the node moves in a predictable pattern. HLP has the least localization frequency because it detects the low speed and predictable pattern of the sensor and sets the localization period accordingly.

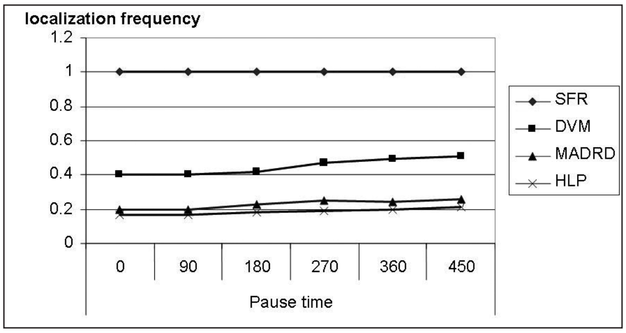

Fig. 7. Localization frequency at 1 m/sec speed.

The fourth experiment compares the effect of varying sensor's speed on the energy consumption for SFR, DVM, MADRD and HLP. The pause time is fixed at 90 seconds. Figure (8) plots the localization frequency of the protocols as a function of sensor's speed. Similar to Figure (7), the localization operations are normalized to SFR. As the figure shows, SFR has the highest localization frequency. This is expected since SFR localizes at a fixed frequency regardless of the speed. When the speed is low, SFR has more overhead localization. DVM is more efficient than SFR since it adapts with change in the speed. Because the pause time is quite long, DVM is better than SFR. MADRD consumes less energy than DVM and HLP has the least energy consumption as expected.

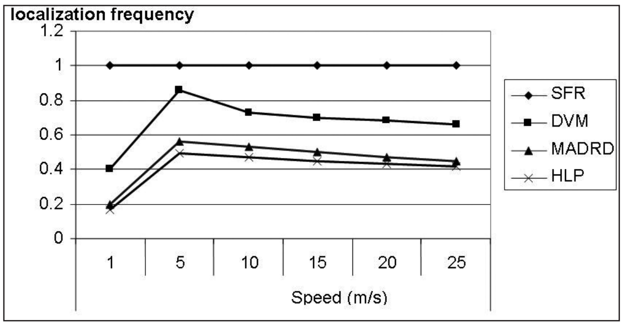

Fig. 8. Localization frequency at 90 pause time.

The fifth experiment compares the effect of varying the pause time on the accuracy of SFR, DVM, MADRD and HLP. The speed is fixed at 5 m/sec. Figure (9) plots the mean absolute error (MAE) of the protocols as a function of pause time. The MAE is a quantity used to measure how close the calculated values are to the actual measurement values. The MAE is given by

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i|$$

Where:

f_i is the predicted (simulated or calculated) value of the node location;

y_i is the true (measured) value of the node location;

$e_i = f_i - y_i$, is the absolute error; and

n is the number of nodes.

As Figure (9) shows, HLP achieves the highest accuracy compared to its SFR, DVM and MADRD counterparts. This is expected since HLP calculates the localization frequency adaptively based on both sensor's speed and mobility predictability.

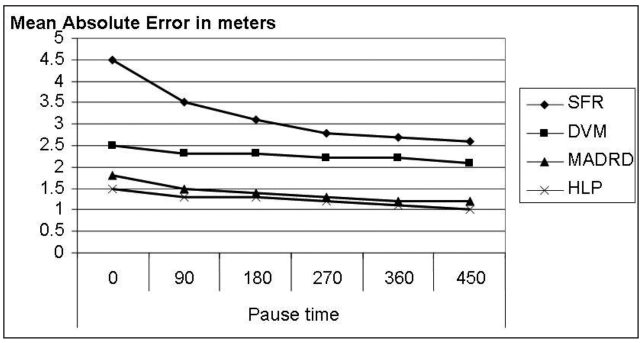

Fig. 9. Mean absolute error at 5 m/sec speed.

The sixth and final experiment compares the effect of varying the sensor's speed on the accuracy of SFR, DVM, MADRD and HLP. The pause time is fixed at 90 seconds. Figure (10) plots the mean absolute error of the protocols as a function of sensor's speed. As the figure shows, HLP achieves the highest accuracy compared to its SFR, DVM and MADRD counterparts. This is expected since HLP calculates the localization frequency adaptively based on both sensor's speed and mobility predictability.

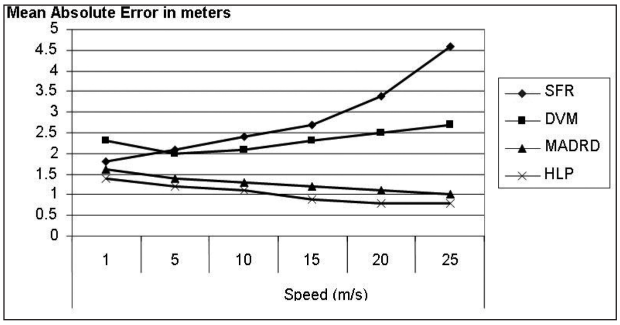

Fig. 10. Mean absolute error at 90 sec pause time.

CONCLUSION

In this research we propose an efficient Hybrid Localization Protocol (HLP) for mobile sensor networks that dynamically invokes adaptive and predictive protocols based on some heuristics. HLP determines the optimal time period of the localization process based on the sensor's speed and mobility pattern predictability. Optimal time period of localization reduces the energy consumption of localization while increasing the localization accuracy. We developed a Java-based simulation model to simulate the proposed protocol and to compare its performance with static, adaptive and predictive protocols. We compared the performance of HLP with that of SFR, DVM and MADRD in regards to localization error and energy efficiency. Experimental Simulation results and analysis show that the proposed protocol is more efficient than the existing counterpart protocols.

ACKNOWLEDGEMENT

The author would like to thank the deanery of scientific research at the Islamic University of

Gaza (IUG) for their support, his graduate student Fidaa Abed from the Electrical and Computer Engineering Department at the Islamic university of Gaza, Gaza, Palestine, for his useful feedback and comments during the preparation of this paper.

REFERENCES

Bachrach, J, and **Taylor, C** (2005) Localization in Sensor Networks. *In:* **Stojmenović, I**. *Handbook of Sensor Networks*. Wiley Press, NewYork, USA. Not complete,

Bulusu N, Heidemann, J, and **Estrin, D** (2001) **Density Adaptive Algorithms for Beacon Placement in Wireless Sensor Networks.** IEEE ICDCS 2001, April 2001.

Bulusu, N, Heidemann, J, and **Estrin, D** (2000) *Gps-less Low Cost Outdoor Localization for Very Small Devices*. IEEE Personal Communications Magazine 7, 5 October 2000.

Doherty, L, Pister, K, and **ElGhaoui, L** (2001) *Convex Position Estimation in Wireless Sensor Networks*. IEEE Info. Com. 2001. April 2001.

Estrin, D, Culler, D, Pister, K, and **Sukhatme, G** (2002) Connecting the Physical World with Pervasive Networks. **IEEE Pervasive Computing 1(1):** pp. 59-69.

Estrin, D, Girod, L, Potti, G, and **Srivastava, M** (2001) Instrumenting the World with Wireless Sensor Network. *In: Proceedings of ICASSP'2001*, pp. 2675-2678.

He, T, Huang, C, Blum, B, Stankovic J, and **Abdelzaher, T** (2003) Range-free Localization Schemes for Large Scale Sensor Networks. *In: Proceedings of 9th annual internatonal conference on mobile computing and networking*. Sep 2003, pp.81–95.

Hill, J, Szewczyk, R, Woo, A, Hollar, S, Culler, D, and **Pister, K** (2000) System Architecture Directions for Networked Sensors. *In: Proceedings of ASPLOSIX.*, pp. 93-104.

Hu, L, and **Evans, D** (2004) Localization for Mobile Sensor Networks. *In*: *Proceedings of the 10th Annual international Conference on Mobile Computing and Networking*. (Mobi. Com '04, ACM), Philadelphia, PA, USA, September 26 - October 01, 2004, , New York, pp. 45-57.

Juang, P, Oki, H, Wang, Y, Martonosi, M, Peh, L, and **Rubenstein, D** (2002) Energy-Efficient Computing for Wildlife Tracking: Design Tradeoffs and Early Experiences With ZebraNet. *In:Proceedings of ASPLOS-X*. San Jose, pp. 96-107.

KO, Y, and **Vaidya, N** (1998) Location-Aided Routing in Mobile Ad Hoc Networks. *In: Proceedings of the 4th annual ACM/IEEE international conference on Mobile computing and networking*. ACM Press, pp. 66–75.

Li, D, Wong, K, Hu, Y, and **Sayeed, A** (2002) Detection, Classification and Tracking of Targets. *IEEE Signal Processing Magazine* **19:** 17–29.

Nagpal, R, Shrobe, H, and **Bachrach, J** (2003) *Organizing a Global Coordinate System from Local Information on an Ad Hoc Sensor Network*. 2nd International Workshop on Information Processing in Sensor Networks (IPSN). April 2003.

Niculescu, D, and **Nath, B** (2003) DV Based Positioning in Ad hoc Networks. *Kluwer Journal of Telecommunication Systems* **22 (1-4):** 267–280

Niculescu, D, and **Nath, B** (2003) *Ad Hoc Positioning System (APS) Using AoA*. IEEE Info. Com. 2003.

Patwari, N, and **Hero, A** (2003) *Using Proximity and Quantized RSS for Sensor Localization in Wireless Networks*. Workshop on Wireless Sensor Networks and Applications, September 2003.

Ramadurai, V, and **Sichitiu, M** (2003) Localization in Wireless Sensor Networks: A Probabilistic Approach. *In: International Conference on Wireless Networks*, pp. 275-28.

Savvides, A, Han, C, and **Strivastava, M** (2001) Dynamic Fine-grained Localization in Ad-Hoc Networks of Sensors. *In: Proceedings of ACM MobiCom'01*. Rome, Italy, July 2001, pp. 166-179.

Shang, Y, Ruml, W, Zhang, Y, and **Fromherz, M** (2003) *Localization from Mere Connectivity*. Mobi. Hoc 2003, June 2003.

Sheng, X, and **Hu, Y** (2003) *Collaborative Source Localization in Wireless Sensor Network System*. IEEE Globe.com.

Stoleru, R, Stankovic, J, and **Son, S** (2007)

Robust Node Localization for Wireless Sensor Networks. *In: Proceedings of the 4th workshop on Embedded networked sensors*. June 25-26, 2007, Cork, Ireland.

Tila, S, Kolar, V, Abu-Ghazaleh, N, and **Kang, K** (2005) *Dynamic Localization Protocols for Mobile Sensor Networks,* IEEE IWSEEASN.

Wellenhoff, B, Lichtenegger, H, and **Collins, J** (1997) *Global Positioning System: Theory and Practice*. (4 edn.), Springer Verlag.

Yi, J, Yang, S, and **Cha, H** (2007) Multi-hop-based Monte Carlo Localization for Mobile Sensor Networks. *In: 4th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Network* (SECON '07), 18-21 June 2007, pp.162-171

Ref. No. (2490)
Rec. 25/06/2008
In-revised form: 26/01/2009