Scalable Localization with Mobility Prediction for Underwater Sensor Networks

Zhong Zhou†, Jun-Hong Cui† and Amvrossios Bagtzoglou‡
{*zhongzhou, jcui, acb*}*@engr.uconn.edu*
†Computer Science & Engineering, University of Connecticut
‡Civil & Environmental Engineering, University of Connecticut

***Abstract*—Due to adverse aqueous environments, non-negligible node mobility and large network scale, localization for large-scale mobile underwater sensor networks is very challenging. In this paper, by utilizing the predictable mobility patterns of underwater objects, we propose a scheme, called Scalable Localization scheme with Mobility Prediction (SLMP), for underwater sensor networks. In SLMP, localization is performed in a hierarchical way, and the whole localization process is divided into two parts: anchor node localization and ordinary node localization. During the localization process, every node predicts its future mobility pattern according to its past known location information, and it can estimate its future location based on its predicted mobility pattern. Anchor nodes with known locations in the network will control the whole localization process in order to balance the tradeoff between localization accuracy, localization coverage and communication cost. We conduct extensive simulations, and our results show that SLMP can greatly reduce localization communication cost while maintaining relatively high localization coverage and localization accuracy.**

I. Introduction

Last several years have overseen a rapidly growing interest in underwater sensor networks [1], [6], [9], [12]. One important reason is because they can offer significant advantages and benefits in a wide spectrum of aquatic applications: underwater environmental observation for scientific exploration, commercial exploitation, and coastline protection and target detection in military or terrorist events.

Localization of mobile sensor nodes is indispensable for underwater sensor networks. For example, in aquatic environment monitoring applications, localization is a must-do task in order to get useful location-aware data. Location information is also required for geo-routing, which is proved to be more scalable and efficient in mobile underwater sensor networks [14]. So far, only a limited number of schemes have been proposed for the localization service in underwater acoustic networks [2], [4], [7], [15]. These solutions are mainly designed for small-scale static networks (usually with tens of nodes or even less). However, many aquatic applications, such as marine surveillance, requires a localization solution that can scale to a large number (hundreds to thousands) of nodes. In this paper, we focus on the localization service for large-scale mobile underwater sensor networks.

Due to adverse aqueous environments, non-negligible node mobility and large network scale, localization for large-scale mobile underwater sensor networks is very challenging. Since radio does not work in water, acoustic communications have to be employed. The unique features of acoustic channels (large-latency, low-bandwidth, and long end-to-end delays) cause many constraints on the localization schemes for underwater sensor networks. Traditional multi-hop localization schemes for terrestrial sensor networks are inefficient because of their huge communication overhead. Meanwhile, underwater sensor networks are mobile networks and node locations change continuously. In such environments, most localization schemes designed for static sensor networks need to run periodically to update the location results, as will dramatically increase the communication overhead. Further, distributed localization schemes designed for small-scale underwater acoustic networks [7], [15] can not work well in large-scale underwater sensor networks due to their slow convergence speed and high communication overhead.

Though the network conditions in underwater environments are extremely tough for localization (as we discussed above), some unique properties can be indeed effectively exploited. A very useful property we find is that objects underwater move with predictable patterns, though these patterns are in a large part determined by environmental factors [3], [11]. This mobility property can actually provide us an alternative for high performance localization. In this paper, we propose a scheme, called **S***calable* **L***ocalization scheme with* **M***obility* **P***rediction* (**SLMP**), for underwater sensor networks. In SLMP, localization is performed in a hierarchical way, and the whole localization process is divided into two parts: anchor node localization and ordinary node localization. During the localization process, every node predicts its future mobility pattern according to its past known location information, and it can estimate its future location based on its predicted mobility pattern. Anchor nodes with known locations in the network will control the whole localization process in order to balance the tradeoff between localization accuracy, localization coverage and communication cost. Simulation results show that SLMP can greatly reduce localization communication cost while maintaining relatively high localization coverage and localization accuracy.

The rest of this paper is organized as follows. In Section II, we will give some background knowledge on underwater object mobility. Then, in Section III, we will describe SLMP in details using seashore environments as an example. Following that, we present simulation results in Section IV. Finally, we conclude the paper in Section V.

II. Mobility Characteristics of Underwater Objects

Underwater objects are moving continuously with water currents and dispersion. Research in hydrodynamics shows that the movement of underwater objects is closely related to many environment factors such as the water current, water temperature [3], [11]. In different environments, the mobility characteristics of underwater objects are different. Some mobility models for underwater objects in specific environments based on hydrodynamics have been devised [3], [11]. This indicates that the movement of underwater objects is not a totally random process. Temporal and spatial correlation are inherent in such movement, as makes their mobility patterns predictable in nature.

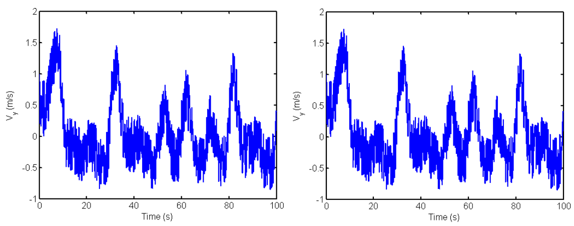


Fig. 1. Mobility patterns in a seashore environment

As a case study, in this paper, we will investigate the mobility characteristics of objects in shallow seashore areas (referred to as *seashore environments* in this paper). Fig. 1 shows the velocity of an underwater object with time in a typical seashore environment. We can clearly see that the moving speed of the object changes continuously and shows certain semi-periodic property. This is mainly due to the tides and bathymetry. The exhibited strong time-domain correlations tell us that it is possible to estimate the future value based on the measured past values with high accuracy[1]. Further, [11] and [3] show that spatial correlations exist in underwater environments, which means that the movement of one object is closely related to its nearby objects. In other words, underwater objects possess certain group movement properties.

III. Description of SLMP

In this section, we present SLMP, a scalable localization scheme with mobility prediction for underwater sensor networks. We will first describe the network architecture, and give an overview of SLMP. We then show how SLMP works in details using the mobility patterns in seashore environments.

A. Network Architecture

To accomplish the localization task for large-scale underwater sensor networks, we propose a network architecture that comprises of three different types of nodes, as shown in Fig. 2.

- *Surface Buoys*. Surface buoys are equipped with GPS to obtain their location estimates. They serve as the "satellite nodes" in underwater localization schemes.
- *Anchor Nodes*. Anchor nodes are powerful nodes which can make direct contact with the surface buoys, and are capable of self-localization based on such contacts.
- *Ordinary Nodes*. Ordinary sensor nodes are low-complexity sensor nodes which cannot directly communicate with surface buoys – they are cheap, and they do not wish to be profligate with their energy. Typically, the ordinary sensor nodes can only connect to its local (usually one-hop) neighbors. Through local message passing among themselves and with nearby anchor nodes, the ordinary sensor nodes desire to self-localize so that they can effectively participate in the network operation.

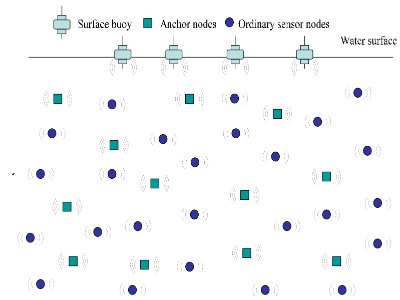


Fig. 2. Underwater sensor network architecture

In the target network, we assume that every sensor node needs to get its location periodically. We define the period each node needs to get its location as *localization period*, denoted as T_1.

B. Overview of SLMP

SLMP uses a hierarchical localization approach. The whole localization process is divided into two sub-processes: anchor node localization and ordinary node localization.

At the beginning, only several surface buoys know their locations through common GPS or by other means. Four or more buoys are needed in our system. These buoys work as the "satellites" for the whole network and anchor nodes can be localized by these surface buoys. Since anchor nodes are more powerful and can measure their locations directly from the surface buoys in every localization period, some complicated mobility prediction algorithms can also be implemented on them. For the ordinary node localization, we propose a distributed recursive range-based scheme which will be described in Section III-D in details. Since ordinary nodes are limited in computation power and memory, it is hard to implement complicated prediction algorithms on them. Fortunately, due to the group movement properties of underwater objects, an ordinary node can deduce its mobility pattern from the mobility patterns of nodes nearby.

C. Anchor Node Mobility Prediction

Anchor nodes can easily measure their locations directly at any localization period since they can directly communicate with the surface buoys, and they could also predict their future mobility patterns based on their past measurements.

From Fig. 1, we can observe that the moving speed of the underwater object in seashore environments changes continuously and demonstrates certain semi-periodical properties. We also notice that its waveform is very similar to that of the voice signal. It is well known that the voice signal can be closely approximated by an all-pole model and thus can be

[1] In this paper, we assume that objects keep constant in z (depth) axis, and the mobility pattern of objects is only related to the (x, y) axis. Thus, objects with the same (x, y) but different z move with the same mobility pattern. This is a common assumption in hydrodynamics [3], [11]

well predicted by linear prediction algorithm [8], [13]. Inspired by this, we adopt the linear prediction method in our system for anchor node mobility prediction. It works as follows.

First, we divide time into multiple *prediction windows* with length set to T_w. One window is one prediction unit. We assume that the mobility behaviors of the nodes will not change during adjacent prediction windows. This is a reasonable assumption considering the continuity and the semi-periodicity of the underlying mobility behavior. Thus we can use measured values in the previous window to predict the mobility behavior of the next window. Window length T_w should be integer times of the localization period T_1.We denote this as $T_w = k \times T_1$. To further improve the accuracy of our prediction, neighboring windows should be overlapped to some extent to avoid the edge effects of the windowing operation [8], [13]. We set $\varsigma = \frac{T_l}{T_w}$ and the typical value for ς is from 0.1 to 0.5.

For every node, we use speed vector $V = [v(1), v(2), \dots v(i), \dots, v(k)]$ to represent its mobility behavior in every prediction window, where $v(i)$ denotes the average speed in the ith localization period. In order to predict $v(i)$, we use a linear prediction algorithm as follows:

$$v(i) = \sum\nolimits_{m=0}^{l} a_m v(i-m), \tag{1}$$

where l is the length of prediction steps, and a_m is the linear prediction model coefficient between $v(i)$ and $v(i-m)$. a_m's can be estimated by using measured location data from previous windows. In our work, we use the well known Durbin algorithm [13] to estimate them. We choose Durbin algorithm mainly because of its simplicity and low computation complexity $O(l^2)$, where l is the length of prediction steps.

In localization period i, an anchor node can measure its actual location $Loc_a(i)$ and calculate its estimated location $Loc_e(i)$ as follows:

$$Loc_e(i) = Loc_a(j) + \sum_{m=j}^{i} T_1 \times v(m), \tag{2}$$

where $Loc_a(j)$ is the measured location in period j.

If the error between the estimated location $Loc_e(i)$ and the measured location $Loc_a(i)$ is smaller than the stipulated threshold s_t, this indicates that the predicted speed vector V works well and there is no need for further action. Otherwise, the current active speed vector V is not so accurate. Then, this anchor node needs to rerun the mobility prediction algorithm to update its speed vector V, and broadcast its current location and predicted speed vector V in one localization message to inform the network.

The structure of an localization message is shown in Fig. 3, where *Node id* is the unique identification number of the message sender; *Time stamp* is the time when this message is sent; *Location* is the current location of the message sender; *Speed vector* is the predicted speed vector for the next window; and *Confidence value*is the confidence value of the message sender. It is used to denote the location estimation accuracy. For original anchor nodes, they are set to be 1. We will discuss how to calculate this value for ordinary nodes later in Section III-D.

Note localization messages could be sent by both anchor nodes and localized ordinary nodes. The later case will be discussed in the next section.

Node-id	Time-stamp	Location	Speed vector	Confidence value

Fig. 3. Localization message structure

D. Ordinary Node Mobility Prediction & Localization

As for ordinary nodes, because of their limited memory and computing capacity, they can not perform complicated temporal prediction algorithms. In SLMP, we take full advantages of the spatial correlation that underwater objects possess to facilitate mobility prediction.

1) Mobility Prediction: Assume we want to get the velocity $[v_x(j), v_y(j)]$ of node j, where $v_x(j)/v_y(j)$ denotes the current speed of node j in the x/y axis. If we get to know the velocities of its neighbor nodes, then we can estimate the velocity of j as follows [3], [11].

$$\begin{cases} v_x(j) = \sum_{i=1}^{m} \zeta_{ij} v_x(i) \\ v_y(j) = \sum_{i=1}^{m} \zeta_{ij} v_y(i) \end{cases}, \tag{3}$$

where m is number of neighbors. The interpolation coefficient ζ_{ij} is calculated as

$$\zeta_{ij} = \frac{\frac{1}{r_{ij}}}{\sum_{i=1}^{m} \frac{1}{r_{ij}}}, \tag{4}$$

where r_{ij} denotes the Euclidean distance between node i and node j.

2) Localization Process: For ordinary nodes, we adopt a recursive localization method. We smoothly incorporate mobility prediction into the localization process.

First, we define *reference nodes* as nodes with known locations and confidence values higher than the confidence threshold. In the *initialization phase*, all anchor nodes label themselves as reference nodes and set their confidence values to 1. All the ordinary nodes are non-localized nodes. With the advance of the localization process, more and more ordinary nodes are localized and become reference nodes. Each ordinary node maintains a reference list to record all its known reference nodes. Each reference node entry in the list includes the following information: the reference node ID; the arrival time of the latest localization message from this reference node; the reference node's location and speed vector, the distance to this reference node; and the confidence value of the reference node.

In each localization period, every node updates its known reference list. This updating process include the following operations:

- Check the arrival time of the latest localization message from every known reference node. If the distance between the current time and the last arrival time is larger than k localization periods, this reference node is too old to be useful, and should be deleted from the list.
- For every known reference node, update its location as follows:

$$Loc(i) = Loc(i-1) + T_1 \times v(i), \tag{5}$$

where $Loc(i)$ denotes the estimated location of this reference node in localization period i and $v(i)$ is the estimated speed of this reference node in localization period i.

- Update the confidence value of every known reference node. To well reflect the network conditions, the confidence value of a known reference node should decrease with time if no new localization message has been received from that reference node. In our simulations, we update the conference value for a reference node as follows:

$$\eta = \frac{k - \frac{(t_{curr} - t_{recv})}{T_1}}{k} \times \eta_0, \tag{6}$$

where t_{curr} denotes the current time; t_{recv} denotes the arrival time of the latest localization message from this reference node; and η_0 is the old confidence value obtained from the last localization message.

In a localization period, for any non-localized ordinary node, if it does not receive any localization message, it will update its current location estimation by using its previous location estimation and its predicted speed vector. If it receives a localization message from one reference node, it will update its reference list and perform new location estimations. Readers can refer to our technical report for more details [16].

IV. Simulation Results

In this section, we evaluate the performance of SLMP through simulations.

A. Simulation Settings

In our simulations, 500 sensor nodes are randomly distributed in a $100m \times 100m \times 100m$ region. We define node density as the expected number of nodes in a node's neighborhood. Hence node density is equivalent to node degree. We control the node density by changing the communication range, R, of every node while keeping the area of deployment the same. Range (i.e., distance) measurements between nodes are assumed to follow normal distributions with real distances as mean values and standard deviations to be two percent of real distances. This is a reasonable assumptions and can be easily satisfied by existing underwater distance measurement technologies [4], [10]. 5%, 10% and 20% anchor nodes are considered in our simulations. Besides SLMP, we also simulate one localization scheme without mobility prediction for comparison. The localization process of this scheme is almost the same as that of SLMP, except that it does not involves mobility prediction. As to the node mobility pattern, we consider the kinematic model in [5]. Readers can refer our technical report for more details [16].

Unless specified otherwise, we have the following parameters. Localization period T_1 is set to be 1s. The prediction error threshold of anchors s_t is set to be $0.05R$. The length of prediction steps l is set to be 15. The prediction window size T_w is set to be 60s and $\varsigma = 0.2$. The confidence threshold of ordinary node λ is set to be 0.98.

Three performance metrics are considered in our simulations: localization coverage, localization error and average communication cost. *Localization coverage* is defined as the ratio of the localizable nodes to the total nodes. *Localization error* is the average distance between the estimated positions and the real positions of all nodes. For our simulations, we normalize this absolute localization error to the node's communication range R. *Average communication cost* is defined as the overall messages exchanged in the network divided by the number of localized sensor nodes.

B. Results and Analysis

1) Performance with Changing Node Density: In this set of simulations, we set the anchor percentage to be 10% and change the average node density from 8 to 16 by changing the node range R.

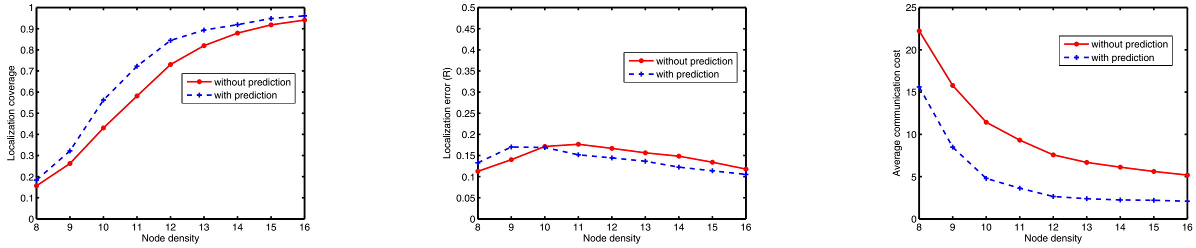
Without surprise, Fig. 4(a) shows us that the localization coverage increases monotonically with node density. Further, the localization coverage of our scheme with prediction (i.e., SLMP) is higher than that of the scheme without prediction. This is because with mobility prediction, some nodes which can not get located in current network conditions can be localized by the prediction scheme. Thus, compared with the scheme without mobility prediction which needs to redo one complete localization process in every localization period independently, our scheme can even achieve higher localization coverage.

Fig. 4(b) shows us that with the increase of node density, the average localization error of our scheme will first increase a little and then it will decrease monotonically. We think that the increase in the lower node density region is due to the rapid increase of the corresponding localization coverage. While when the node density reaches a certain point, most localizable nodes get located. With the further increase of node density, un-localized nodes will get to know more reference nodes and have more choices to calculate their locations. Thus, the localization error will reduce.

Fig. 4(c) clearly shows us that with the increase of node density, the average communication cost decreases rapid first. This is because with the increase of node density, the localization coverage increases drastically. Thus the average communication cost decreases rapidly. Further, we can observe that when the node density increases to some point, for example, in Fig.4(c), when it increases to 12, the average communication cost will stabilize to some small values. Fig. 4(c) also shows us that our mobility prediction scheme can greatly reduce the communication cost. This is reasonable since in our scheme, anchor nodes need not send localization message in every localization period and thus limit the frequency of localization message flooding. Correspondingly, the overall communication cost is reduced. This is quite meaningful for underwater sensor networks with limited bandwidth and energy.

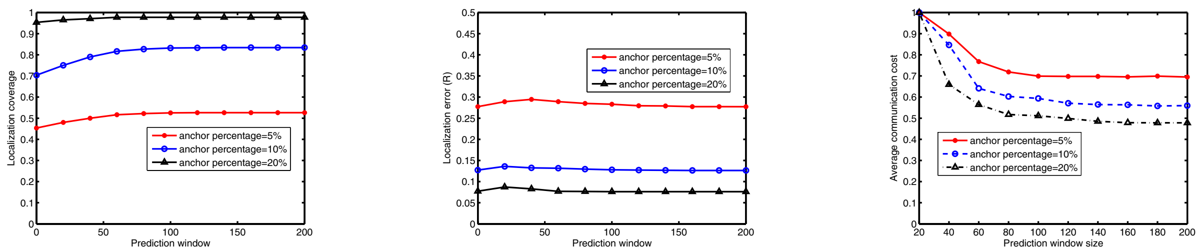
2) Performance with Changing Prediction Window T_w: In this set of simulations, node range R is fixed to be 20m and thus the average node degree is about 12. We change the prediction window T_w from 20s to 200s. Here, in order to show the advantages of mobility prediction, we normalize the average communication cost to that of localization scheme without mobility prediction.

Fig. 5 shows that with the increase of prediction window, the localization coverage increases slightly. At the same time, the localization error decreases a little. This is because the larger the window size, the more accurate the prediction results for anchor nodes, as will cause more ordinary nodes to become reference nodes and thus the localization coverage of the whole network increases and the localization error decreases slightly.



(a) Localization coverage (b) Localization error (c) Communication cost

Fig. 4. Performance with changing node density



(a) Localization coverage (b) Localization error (c) Normalized communication cost

Fig. 5. Performance with changing prediction window

As shown in Fig. 5, the normalized average communication cost decreases monotonically with the prediction window. This is reasonable since more accurate prediction results mean less traffic that anchor nodes send out. But when the prediction window reaches some large value, for example, 100s for the case of 10% percent of anchor nodes, increasing prediction window will not contribute much to the reduction of communication cost. This is because in such situations, the communication cost of the localization process is dominated by the localization messages among ordinary nodes as well as the beacon messages which are used to measure distance among nodes periodically.

We have also conducted simulations to evaluate the various design parameters of SLMP, such as the prediction error threshold s_t, the length of prediction steps l and the confidence threshold of ordinary nodes λ. Due to space limitation, these results are not included in this paper. Interested readers can refer to our technical report [16].

V. Conclusions

In this paper, we have presented SLMP, a new localization scheme with mobility prediction, for large scale underwater sensor networks. In SLMP, anchor nodes conduct linear prediction by taking advantages of the inherent temporal correlation of underwater object mobility pattern. While each ordinary sensor node predicts its location by utilizing the spatial correlation of underwater object mobility pattern, weighted-averaging its received mobilities from other nodes. Our simulation results show that SLMP can greatly reduce the communication cost while maintaining a relatively high localization coverage and localization accuracy.

References

[1] I. F. Akyildiz, D. Pompili, and T. Melodia. Underwater acoustic sensor networks: Research challenges. *Ad Hoc Networks (Elsevier)*, 3(3):257–279, March 2005.

[2] T. C. Austin, R. P. Stokey, and K. M. Sharp. PARADIGM: a buoy-based system for auv navigation and tracking. In *IEEE Proceedings of Oceans*, 2000.

[3] A. C. .Bagtzoglou and N. A. Chaotic behavior and pollution dispersion characteristics in engineered tidal embayments: A numerical investigation. *Journal of the American Water Resources Association*, pages 207–219, 2007.

[4] C. Bechaz and H. Thomas. GIB system: The underwater gps solution. In *Proceedings of ECUA*, May 2001.

[5] S. P. Beerens, H. Ridderinkhof, and J. Zimmerman. An analytical study of chaotic stirring in tidal areas. *Chaos, Solitons and Fractals*, 1994.

[6] J.-H. Cui, J. Kong, M. Gerla, and S. Zhou. Challenges: Building scalable mobile underwater wireless sensor networks for aquatic applications. *IEEE Network, Special Issue on Wireless Sensor Networking*, 20(3):12–18, 2006.

[7] J. E. Garcia. Ad hoc positioning for sensors in underwater acoustic networks. In *IEEE Proceedings of Oceans*, 2004.

[8] S. Goronzy. *Robust Adaptation to Non-Native Accents in Automatic Speech Recognition*. Springer Berlin / Heidelberg, 2002.

[9] J. Heidemann, Y. Li, A. Syed, J. Wills, and W. Ye. Research challenges and applications for underwater sensor networking. In *Proc. of the IEEE Wireless Communications and Networking Conference (WCNC)*, 2006.

[10] N. H. Kussat, C. D. Chadwell, and R. Zimmerman. Absolute positioning of an autonomous underwater vehilce using GPS and acoustic measurements. *IEEE Journal of Oceanic Engineering*, 30(1):153–164, Jan 2005.

[11] A. Novikov and A. C. Bagtzoglou. Hydrodynamic model of the lower hudson river estuarine system and its application for water quality management. *Water Resource Management*, pages 257–276, 2006.

[12] J. Partan, J. Kurose, and B. N. Levine. A Survey of Practical Issues in Underwater Networks. In *Proc. of ACM International Workshop on UnderWater Networks (WUWNet)*, pages 17–24, September 2006.

[13] L. R. Rabiner and R. W. Schafer. *Digital processing of Speech Signals*. Prentice-Hall,Inc, Engelwood Cliffs, New Jersey, 1978.

[14] P. Xie, L. Lao, and J.-H. Cui. VBF: vector-based forwarding protocol for underwater sensor networks. In *To appear in Proceedings of IFIP Networking*, May 2006.

[15] Y. Zhang and L. Cheng. A distributed protocol for multi-hop underwater robot positioning. In *IEEE Proceedings of International Conference on Robotics and Biomimetics*, 2004.

[16] Z. Zhou, J.-H. Cui, and A. Bagtzoglou. Scalable localization with mobility prediction for underwater sensor networks. *UCONN CSE Technical Report: UbiNet-TR07-01, http://www.cse.uconn.edu/ jcui/publications.html*, July 2007.