Indoor Positioning: Group Mutual Positioning

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ABSTRACT

People often visit public spaces such as shopping malls and museums in small groups. Ubiquitous computing will shortly allow tracking, monitoring and supporting individuals and groups in such spaces. Positioning data can then be used by an inference mechanism to capture the abstract meanings that underline the measurements, and represent the social context of real world small groups of people, located indoor, within a virtual world. However, current real world sensors are limited, leading to conditions where some measurements are lost, and some areas may not be covered by sensors. Sensors data should (and probably will) be augmented with inference mechanisms to overcome missing data and resolve conflicts. In the case of positioning, proximity measurements enable the assessment of the relative position of people. The synergetic combination of the proximity measurements and the direct positioning information can enable an inference mechanism to compensate for missing measurements and improve overall positioning data.

Author Keywords

Indoor Positioning, Social Signal Processing.

ACM Classification Keywords

H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

Imagine being a miner in a Chilean mine trapped underground for the next two months; being onboard a US Navy carrier for the next 6 months; space travelling for the next year; or restricted to your home or to a hospital bed. In all of these cases you may enjoy a video call with your loved ones. However, you cannot enjoy a shared experience with your loved ones in a dynamic environment such as their nearest mall or museum. Now imagine a futuristic application that may enable you to join your loved ones in such a remote shared experience. This would require representation of the social context as part of the virtual presence of real world people within the virtual world. The other side of the coin is to enable social presence of a virtual agent in the real world for the benefit of the real world people. This requires mixed reality applications where the real world is represented in the virtual world and the virtual world is represented in the real world. Such applications would require measurements, inference and modeling of real world people. The type of data that is needed for such applications is **accurate** and **continuous** indoor positioning and proximity of the people involved [Mennecke et al., 2008] (in order to provide realistic representation of the real world in the virtual one).

Today's indoor positioning solutions are not perfect [Varshavsky and Patel, 2010]. Depending upon the technology, data may be incomplete, erroneous or simply inaccurate. Sometimes positioning messages might get lost or leave gaps in the positioning information. There are cases where partial information such as being in close proximity to a group of people may enable mutual updates of position (where accurate positioning data is not available). That is if A is near B, the position of A is unknown and the position of B is known, we may be able to infer the position of A from the position of B. The problem with current indoor positioning technologies is that they do not support the requirements for continuous and complete information [Meguerdichian, 2001; Varshavsky and Patel, 2010]. In order to improve current position measurements, we suggest using complementary information available by the social context of people in close proximity to a person whose position is known. This involves augmenting indoor positioning with social signal processing reasoning. We used the instrumentation, installed at the Hecht Museum[1] for the PIL mobile museum guide project [Kuflik et al., to appear], to analyze possible contributions of social context to positioning. Among its services, the PIL system enables measurements of positions of individuals and group members. This positioning data was used to demonstrate how social proximity-based positioning can improve overall positioning.

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[1] http://mushecht.haifa.ac.il/info_eng.aspx, accessed Sep 30th 2010

BACKGROUND

Over the years, a variety of technologies have been experimented for indoor positioning in places such as warehouses, hospitals, shopping malls, manufacturing floors, smart houses and museums. These technologies include sensors such as visual camera positioning [Varshavsky and Patel, 2010], various implementations of Radio Frequency Identification (RFID) [Khoury and Kamat, 2009], indoor GPS [Khoury and Kamat, 2009], WiFi based positioning [Khoury and Kamat, 2009], Bluetooth [Hallberg et al., 2003], Ultrasound[2], inertial navigation based on accelerometers for motion detection [Evennou and Marx, 2006], active floor [Varshavsky and Patel, 2010], power line positioning [Varshavsky and Patel, 2010], airbus (detecting changes of pressure or air conditioning flow due to presence or movement) [Varshavsky and Patel, 2010], and other technologies applied for that purpose. Location estimation may use processing tools such as: Proximity measurements (closeness to a device, based on the device detection range), Trilateration (measuring the distance between a device and a number of reference points at a known location), Time-of-Flight (estimating the time-of-flight of a signal between a device and a reference point, based on the speed of light or the speed of sound), Signal Strength Attenuation (by estimating distance based on the decrease in the strength of a signal as it travels away from the signal source), and dead reckoning (prediction of future position in the lack of measurements, based on the last known position, direction and average velocity) [Varshavsky and Patel, 2010]. In many cases positioning sensors are integrated into sensor networks using protocols such as ZigBee [Skibniewski, 2006].

Some studies focused on the accuracy of the measurements [Khoury and Kamat, 2009]. Others e.g. [Meguerdichian, 2001] referred to the question of quality of service, and especially the important questions of measurement coverage. "Holes" in coverage may be a result of several causes: "holes" in space (undetected / uncovered areas), "holes" in time (lost positioning messages) and "holes" in the sensor network (some areas within the sensor network do not forward messages due to low energy of the node, causing messages to travel through a longer path or to be lost) [Fang et al., 2006].

Since "holes" in measurements pose major challenge to positioning systems, the use of complementary information from other sensors in the vicinity may help reduce their effect. In our case, such complementary information may be found in the analysis of the social context. That is if A is near B, the position of A is unknown and the position of B is known, we may be able to infer the position of A from the position of B

2 http://www.sonitor.com/technology accessed Oct 3rd, 2010

SOCIAL SIGNAL PROCESSING

Social signal processing is a novel field of study that seeks ways to measure, assess, model and improve human social-behavior by the use of technology that exploits non-verbal cues such as location, facial expressions, eye gaze, gestures, postures, and body language [Caridakis, 2010; Kim et al., 2007; Mancas, 2009; Nakano and Ishii, 2010]. An example of improved group behavior is given by Kim et al. [2007]. It is based on the sociometric badge, a sensor which enables measurement of organizational behavior through conversation, location and acceleration. The researchers used the sociometric badge to assess quality of discussion and to deliver feedback in real-time to the participants in the discussion. Technologies such as the sociometric badge can be used for Organizational Social Engineering to assess human social behavior in organizations [Ara et al., 2008; Olgu´ın et. al, 2009; Waber et al., 2007]. The sociometric badge in this case enables feedback to management and employees, based on the physical location of workers within the organization's buildings during work hours and based on the interaction between workers.

PIL POSITIONING SYSTEM

Given the fact that there is no commonly acceptable indoor positioning solution, the PIL project provided a solution that minimizes the installation complexity while providing acceptable accuracy of being within 1.5 to 2 meters from the object of interest (illustrated by Fig. 1, bottom, left). The Hecht museum is equipped with a Radio Frequency (RF) based positioning system based on a wireless sensor network (WSN) composed by RF devices designed and produced by Tretec[3]. The WSN operates on the 2.4GHz ISM band and is based on 802.15.4 protocol, the underlying layer of the well known ZigBee protocol. The 802.15.4 WSN is formed by three different kinds of objects: fixed RF tags called *Beacons* (Fig. 1, top, right), small (matchbox size) mobile RF tags called *Blinds* (Fig. 1, top, left) and RF to TCP *Gateways* (Fig. 1 bottom, right). Beacons and Gateways have the same size and are roughly twice the size of a blind.

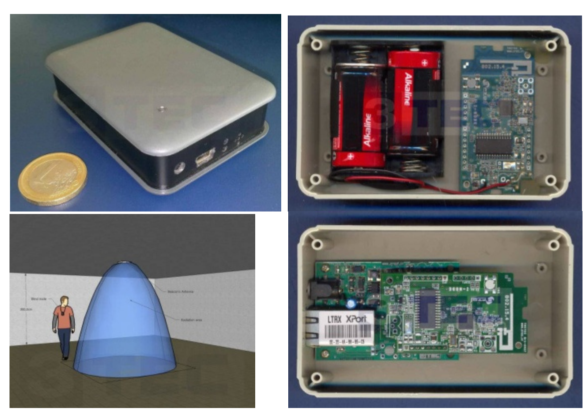

Fig. 1: Positioning device and usage scenario

3 http://www.3tec.it/ accessed Oct 18th 2010

The Gateways transfer the data reported by the Blinds and Beacons' status, over a local area network to the PIL server. Beacons are statically located at entrances and exits, as well as near relevant locations of interest in the museum, while Blinds are carried by visitors (Fig. 1, top, left). When a Blind is in proximity of a Beacon or another Blind, that blind reports this information to the server using the nearest Gateway. The server parses, filters and enhances the information, determining the visitor's position. Another PIL component then decides on actions, e.g. suggesting visitor personalized content adapted to the reported location. It should be noted that in general, several signals may be detected by a blind, so that it can report a number of possible locations with different weights. The ordered set of results, above a given threshold, is sent to the positioning server. The positioning system has several other important features: (i) measuring proximity among Blinds, allowing to reason about the proximity among visitors; (ii) detecting voice level and activity (due to privacy considerations it does not record voice), a feature that can be used to assess the level of conversation among visitors as well as their proximity (people may have a face to face conversation only if they are close to each other), (iii) detecting orientation of visitors, using embedded magnetometers, enabling the assessment of whether visitors are facing each other, the exhibits or standing back to back, and (iv) detecting motion using embedded accelerometers.

THEORETICAL ANALYSIS OF SOCIAL PROXIMITY

Proximity could be translated to a measureable radius around an object, a person, or a group of people. The sensors used by the PIL project (as well as many other indoor positioning sensors) have asymmetric transmission pattern, resulting in better detection in specific directions and poor detection in others. For example, a person's human body shields the transmitted or received signal of a Blind from behind that person if she / he is carrying the Blind on the chest. This makes the proximity detection directional. Therefore there are three options for directional proximity of two people: (1) "A sees B, B does not see A": A is within the transmission pattern of B, and B is not within the transmission pattern of A; (2) "B sees A, and A does not see B": B is within the transmission pattern of A, and A is not within the transmission pattern of B; and (3) "Both A and B see each other": both A and B are within the others transmission pattern (Fig. 2-a). In any of these cases A and B are in close proximity to each other, and this applies for positioning sensors too. When it comes to three sensors or more, the directional proximity is not transitive. Sensor A may be in directional proximity to sensor B who is in directional proximity to sensor C, but sensor A might not detect sensor C (because A is out of C's transmission pattern) (Fig. 2-b). Even if a person A is in directional proximity to both B and C, it does not mean that person C is in close proximity to person B. (Fig. 2-c). In order to conclude that all three sensors A, B and C are in close proximity to each other it is essential to use each pair out of the three sensors separately, to infer about the proximity among the three. (The case where A is in directional proximity to B, B is in directional proximity to C, and C is in directional proximity to A is a private case of the above).

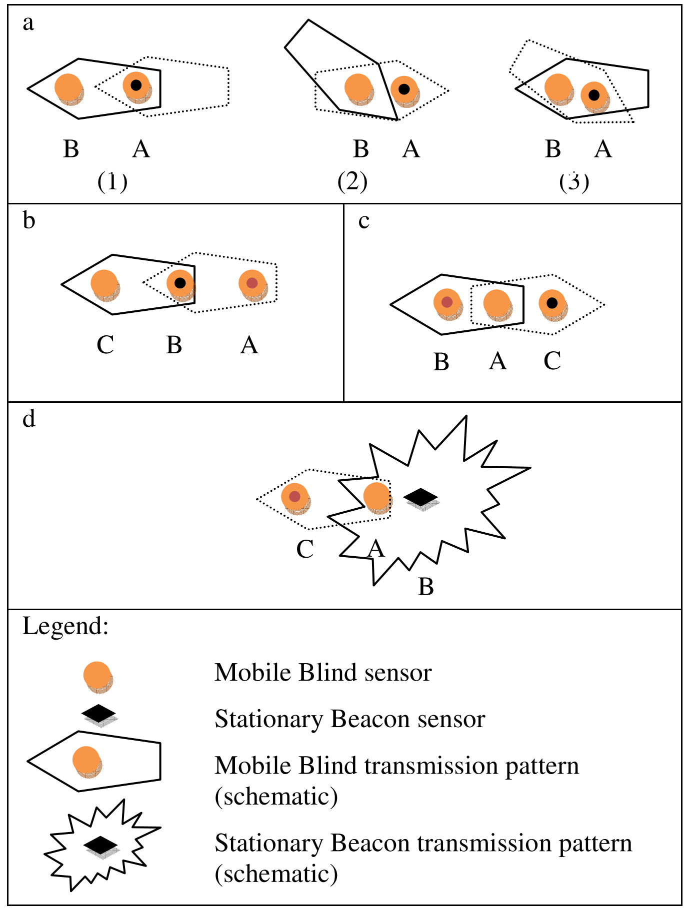

Fig 2. Simplified schematic description of sensor proximity

Position detection at the instrumented Hecht Museum is done by proximity to a location at the museum. This proximity is unidirectional, i.e. a mobile sensor Blind A detects the stationary positioning sensor Beacon B. This means that if another mobile sensor Blind C is in proximity to mobile sensor Blind A, it may still be out of range from the stationary sensor Beacon B (Fig. 2-d). Note that detection occurs when a mobile sensor is within the transmission pattern of a stationary sensor. The bottom line is that proximity between two people, where the position of one of them is directly known, leads to information about the assumed location of the other. This location is known within an uncertainty zone at the size of the proximity pattern around that person (in our case 0.25 to 2 meters).

EVALUATION OF PROXIMITY BASED POSITIONING

The evaluation focused on the positioning of 13 small groups of actual visitors at the Hecht Museum. There were 4 groups of 3 persons and 9 pairs. The visits lasted from 35 minutes to 135 minutes depending on the group (having an average of 64 minutes). During the visits, the museum sensors reported 113,441 reports (39% of the reports – members of groups of three, and 61% – members of groups of two). 11,492 messages (10.1% of all messages) reported proximity to other visitors, out of them 789 messages reported proximity to two visitors. The relatively low percentage of proximity messages is probably due to people separating and not being in close proximity to others during the entire visit time, or due to partial detection of proximity by the mobile Blind sensors. Focusing on the 11,492 messages that had proximity reports, 21% of them had also position report. The other 79% reports did not have a position report. The measured data is reported once a second. Since people walk quite slowly within the museum, it is assumed that positioning and proximity data are still valid within 2 seconds from the time of the report. If the data is older than 2 seconds, it is assumed that it has expired. Therefore this analysis uses only measurements of Blinds that did not have a position of their own, but were in proximity to other blinds (carried by people from the same group), that had a position measurement, which had not expire yet. 899 reports without position data were positioned by using their proximity to part of the 2,427 reports containing a known position, increasing the number of known position reports by 37%.

DISCUSSION AND CONCLUSIONS

Considering proximity of visitors in instrumented space, may contribute to representing their position in the virtual space in several aspects: (1) **Accuracy**– Positioning by proximity of person A to a person B, whose position is known, enables positioning of person A, but this positioning is less accurate then the positioning of person B by the proximity distance. (2) **Coverage and quality-of-service** - If the positioning system quality-of-service and coverage is excellent, the group members would know exactly where they are, and the positioning systems would contribute to the social inference. On the other hand, if the positioning system has partial coverage and suffers from gaps in measurements or reports, mutual social positioning may contribute to improve the positioning data. (3) **The extent of temporal separation of group members** - If group members choose to separate, and are not close to each other a mutual social positioning would not be available. On the other hand if group members choose to be together, social positioning would be available. (4) **Crowding** - crowded places may present both an opportunity to use the position of members of other groups or of individuals for social positioning, but might also overload or shield the positioning system or the sensor network increasing gaps and lost positioning reports. Crowding may also slow people down, enabling inference of social positioning out of a position, measured a little earlier or later than the proximity (The involved people could not quickly separate because of the crowd). (5) **Complementary social factors** – Other social factor such as orientation or conversation (voice detection) may serve in the determination of social positioning too. All the above may enable systems to build a spatial model of visitors to computerized environment, which, in turn, may enable them to communicate and share experience with remote as well as on-site colleagues, as suggested by the motivating scenario.

All the above may allow a system to better monitor users in an instrumented environment. As a result, representation of real visitors in virtual worlds and especially in augmented reality scenarios will be more realistic.

REFERENCES

1. Ara, K., Kanehira, N., Olgu´ın, O. D., Waber, B. N., Kim, T., Mohan, A., Gloor, P., Laubacher, R., Oster, D., Pentland, A., and Yano, K.: Sensible Organizations: Changing Our Businesses and Work Styles Through Sensor Data. In: *Journal of Information Processing, vol. 16.* (2008), 1-12.
2. Caridakis, G., Wagner, J., Raouzaiou, A., Curto, Z., André, E., Karpouzis, K.: A Multimodal Corpus for Gesture Expressivity Analysis. In: *The Conference of Multimodal Corpora: Advances in Capturing, Coding and Analyzing Multimodality, LREC, Malta*, (2010).
3. Evennou, F., Marx,F. Advanced Integration of Wi-Fi and Inertial Navigation Systems for Indoor Mobile Positioning. *EURASIP Journal on Applied Signal Processing.* (2006).
4. Fang, Q., Gao, J., and Guibas, L. J. Locating and Bypassing Holes in Sensor Networks, *Mobile Networks and Applications, Vol. 11(2)*, (2006), 187-200.
5. Hallberg, J., Nilsson, M., Synnes, K. Positioning with Bluetooth. *10th International Conference on Telecommunication ICTEL03, April 2003, Vol. 2,* (2003), 954-958.
6. Khoury, H. and Kamat, V. Evaluation of position tracking technologies for user localization in indoor construction environments, *Automation in Construction* 18, 4 (2009), 444–457.
7. Kuflik, T., Stock, O., Zancanaro, M., Gorfinkel, A., Jbara, S., Kats, S., Sheidin, J. and Kashtan, N. A Visitor's Guide in an "Active Museum": Presentations, Communications, and Reflection. *Journal of Computers and Cultural Heritage.* (to appear).
8. Mancas, M., Glowinski, D., Brunet, P., Cavallero, F., Machy, C., Maes, P. J., Paschalidou, S., Rajagopal, M. K., Schibeci, S., Vincze, L., and Volpe, G.: Hypersocial Museum: Addressing the Social Interaction Challenge with Museum Scenarios and Attention-Based Approaches. *In: QPSR of the numediart research program, Vol. 2, No. 3,* September, (2009), 91-96.
9. Meguerdichian, S., Koushanfar, F., Potkonjak, M., Srivastava, M. B. Coverage Problems in Wireless Ad-hoc Sensor Networks. *In Proc of IEEE Infocom'01, Anchorage, Alaska, U.S.A.*. (2001).
10. Mennecke, B. E., Triplett, J. L., Hassall, L. M., Heer, R. and Conde, Z. J. Embodied Social Presence Theory. *Iowa State University College of Business Working Paper Series,* (2008).
11. Nakano, I. Y., and Ishii, R.: Estimating User's Engagement from Eye-gaze Behaviors in Human-Agent Conversations. . In: *The Proceeding of the 14th International Conference on Intelligent User Interfaces, IUI'2010, Hong Kong, China* (2010).
12. Olgu´ın, O. D., Waber, B. N., Kim, T., Mohan, A., Ara, K., and Pentland, A.: Sensible Organizations: Technology and Methodology for Automatically Measuring Organizational Behavior. In: *IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics, vol. 39. (1)*, (2009).
13. Skibniewski, M.J. and Jang, W.S. Ubiquitous computing: object tracking and monitoring in construction processes utilizing ZigBee networks, *Proceedings of the 23rd International Symposium on Automation and Robotics in Construction (ISARC),* Tokyo, Japan, (2006) 287–292.
14. Varshavsky, A. and Patel, S. Location in Ubiquitous Computing. In: Krumm, J. (edt.), *Ubiquitous Computing Fundamentals, Taylor and Francis Group, Florida,* (2010), 285-319.
15. Waber, B. N., Olgu´ın, O. D., Kim, T., Mohan, A., Ara, K., and Pentland, A.: Organizational Engineering Using Sociometric Badges. In*: International Conference on Network Science, New York, NY*, (2007).