Beyond Position Awareness

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Abstract: Location models are merely based on positional information. Using wireless sensor networks, however, allows us to extract information which can be related to different levels of semantic proximity of different devices. Based on this observation, the paper proposes a semantic proximity hierarchy based on a wireless sensor network. In this paper, we argue that the proposed proximity hierarchy adds a new and complementary dimension to pure positional location information. The paper discusses the proposed hierarchy, gives application examples and some preliminary experimental results.

Keywords: Location awareness; Proximity detection; Sensor fusion; Sensor networks

1. Introduction

In the context of ubiquitous computing, location is often used as a synonym for positional information. Positional information is a rich source for context aware applications. It is also interesting to consider relative positions of different devices, as well as the derivatives of the positional information namely velocity and acceleration. Most often, however, the deployment of positional information is limited by the available precision or the cost for the required infrastructure.

In this paper, we argue that relative proximity of devices is an interesting concept for many context aware applications. Using a variety of sensors, such information can be extracted without the need for expensive infrastructure. Furthermore, sensors add new dimensions to the type of location information one can obtain. In particular, one can extract a semantic proximity measure, which goes beyond and complements the traditional positional information paradigm.

Over the last few years great advances have been made in miniaturization, low-cost and low-power design of electronic devices. A large number of these smart devices could be distributed in the environment, in a planned or *ad hoc* way, enabling the environment to analyze and recognize situations [1], such as movement of people and objects, temperature distribution in the room or sounds in the environment. The proposed semantic proximity hierarchy is an ingredient to extract such situational information.

Section 2 introduces a taxonomy of mutual proximity information on which we build a *semantic proximity hierarchy*. This proximity hierarchy is then compared to the more traditional positional information paradigm. Section 3 shortly gives some example applications, and Section 4 describes some preliminary experimental results.

2. Semantic Proximity Hierarchy

Many systems exist to acquire information about the absolute position of devices. Systems such as GPS only work outdoors, whereas many others require a certain amount of infrastructure to enable decent precision. In many applications, however, relative location or proximity of objects is very useful. Bulusu et al. [2], for example, shows a method that measures time-of-flight of the radio-frequency signal to determine physical proximity. Girod [3] also uses time-of-flight, but of a distinct acoustic signal. These systems, however, only determine physical proximity rather than semantic proximity. The goal of this paper is to propose a semantic proximity hierarchy, which can be modeled and recognized by a set of various sensors.

To develop a semantic proximity hierarchy, Table 1 shows a classification of physical parameters of the environments and objects, which can be measured using different sensors. On the one hand, we distinguish between the dynamics and the static state of the environ-

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Table 1. Physical parameters used to classify a proximity hierarchy

	Environment	Object
Static State	temperature, humidity, pressure, ambient acoustic	orientation, tilt, altitude, light, etc.
Dynamics	motion (person moving), light changes, acoustic (speakers, door slamming, etc.)	acceleration, wind, light changes, etc.

ment, and on the other, between the dynamics and static state of an object.

Each class of physical parameters differs in the way it can be used to estimate proximity. The static state of the environment, which may be summarized as weather conditions, corresponds to the first level and most basic concepts of semantic proximity. Since many different locations may have similar weather conditions without being physically or semantically close, this first level is a rather weak proximity measure.

The second level of proximity is given when different devices detect similar and simultaneous dynamics in the environment. When, for example, a person talks or moves around in the vicinity of several devices, these changes in sound and movement, can be detected and correlated to decide that the devices are indeed in the same physical space.

The third and highest level of semantic proximity is given when the devices are attached to the same object, or when they are moving together. Measuring and correlating the dynamics of several devices such simultaneous movement can be detected. In Holmquist et al. [4], similar movement patterns of two devices are used to establish 'friendship' between devices.

2.1. Discussion of the semantic proximity hierarchy

Unfortunately, the proposed proximity hierarchy is more ambiguous than it may seem at first glance. For example, two devices may be in the same room and have very different temperature readings when one of them is lying in the sun. Or when a photo sensor is covered, the light dynamics might not match for different devices, even though they are in the same room. Similarly, when two devices are near one other but one is wrapped, the received sound might correlate only weakly. These examples show that the modeling and recognition of the different semantic levels of the hierarchy is an interesting research problem. We argue that one can and should use a diverse and complementary set of sensors to obtain accurate proximity estimates.

One might ask then why the proposed proximity hierarchy is interesting. In our opinion, there are at least three reasons: first, the proposed proximity hierarchy adds new and complementary dimensions to pure positional information. Secondly, the available precision of pure positional information might limit its usefulness and the type of applications possible. And thirdly, the proposed proximity does not rely on a particular infrastructure installed in the environment. Whereas there are many different possibilities to obtain positional information, they differ in the precision that can be obtained and in the amount of infrastructure required. Most often, the proposed proximity hierarchy will provide inferior precision with respect to absolute positioning systems. In many interesting application scenarios, however, relative proximity will be extremely useful (potentially paired with a relatively imprecise absolute position).

On the other hand, the proximity hierarchy includes more than just relative position information. Imagine the case where two devices are physically close to each other but in different rooms. Absolute positioning systems might fail to determine if two devices are in the same room. However, by correlating the dynamics of the environment, such as audio, makes it relatively easy to determine if two devices are in the same physical environment. This *qualitative* difference in location information becomes even more apparent in the following scenario: when we open or close the door between two adjacent rooms, the semantic proximity of devices changes, even though their physical proximity does not change. Again, measuring and correlating dynamics of the environment makes it

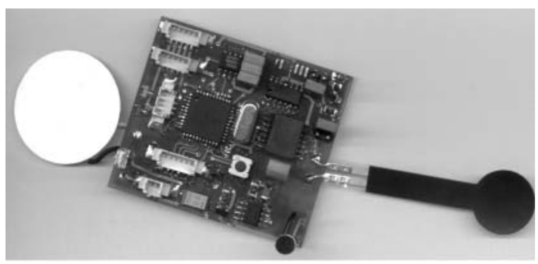

Fig. 1. The Smart-Its sensor board including a microphone, a 2D-accelerometer, a light sensor, a force sensing resistor, and a temperature sensor.

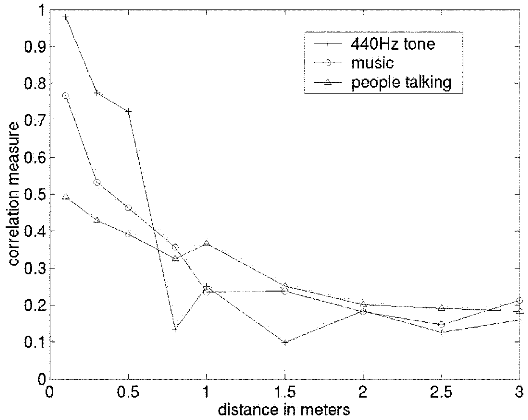

Fig. 2. Correlation measure between two audio signals recorded at distances from 10 cm to 3 m.

relatively easy to distinguish these different levels of semantic proximity.

This brief discussion underlines our claim that positional information and the proposed proximity hierarchy represent different and rather complementary information about the semantic proximity and location of devices.

3. Some Example Applications

The research presented is part of the Smart-Its project (http://www.smart-its.org/).The project's vision is that everyday objects can be enabled as interconnected information artifacts by attaching very small computing devices to them [5]. These devices (Smart-Its) will have memory, computing power, communication with peers, and will be able to perceive their environment using a variety of integrated sensors.

Many applications of devices such as Smart-Its are in the context of monitoring and surveillance. For example, Smart-Its could be used to track chemicals in different stages of their use. There are rules concerning the transport and storage of certain chemicals, such as the amount of heat or vibration that can be tolerated, or which chemicals are allowed to be stored close to each other. Smart-Its could monitor the environmental conditions of each chemical and give warnings when they are not satisfied or are getting critical. Collections of Smart-Its could determine whether dangerous chemicals are close together. Such critical situations could be detected by measuring the relative proximity of chemicals using the proposed proximity hierarchy. A pure positioning system could be used as well, but would require the installation of the appropriate infrastructure everywhere the chemicals might be transported, used, and stored.

Radio Tags and other smart labels may revolutionize logistics and inventory control when used to their fullest potential. However, smart labels are limited since their main functionality is to uniquely identify physical objects in the digital world. Smart-Its devices on the other hand due to their sensing and communication capabilities have many more applications in that domain: Smart-Its may detect which objects are unpacked, which have fallen off the conveyer belt, they may sense if they are still on the road, or if they have been exposed to unacceptable conditions (too hot, too much vibration). With these capabilities fully automated, self-organized inventory control would be possible.

A reoccurring task in many applications is proximity detection of Smart-Its. The proposed proximity hierarchy is a first attempt to classify relations between two or more devices and objects using a variety of sensors. It is important to point out that the proposed proximity hierarchy does not depend upon an infrastructure. This greatly facilitates the deployment of the proposed sensor-based proximity detection. In the following section, we argue that it is not only useful but often necessary to use information coming from multiple sensors. We also give some preliminary experimental results on proximity detection.

4. Preliminary Experimental Results

For the experiments we use the sensor board developed during the Smart-Its project. Figure 1 shows the sensor board, which includes a microphone, a 2D-accelerometer, a light sensor, a force sensing resistor, and a temperature sensor. As means of output it includes a piezo buzzer and three LEDs. To prove the concept of semantic proximity, we conduct two experiments. In a first experiment, we show how the correlation of audio signals can be used to gain proximity information. Then we show how multiple sensors can be used to complement each other. Further experimental results can be found in Antifakos [6].

The goal of the first experiment was to classify whether two Smart-Its are close together or not, based on audio correlation. Using the microphones from two sensor boards, we recorded three different audio signals. First, we recorded a 440Hz standard pitch tone, then we used a music signal, and finally, we recorded people talking. For each audio signal the distance between the sensor boards was varied between 10 centimeters and 3 meters. The results in Fig. 2 show that the signals correlate well up to a distance of about 1 to 1.5 meters.

Since Smart-its might be attached to arbitrary objects, we should take into account the possibility that the audio signals can have very different strength when one or both are wrapped or placed inside a box. We propose, therefore, to differentiate between the following situations: the Smart-Its are (1) close together, (2) close together and (one or both are) in a box, and (3) not close together. Using a photo sensor, we can obtain an appropriate bias to distinguish between situations (1) and (2). The main idea is to correlate the audio signals to get a first proximity estimate, and to use the photo sensors as an extra bias for the situation that the devices are in a box. There were 63 sequences recorded as experimental data, with each sequence having a length of 20 seconds. The auditory environment consisted of office noises such as people talking, someone typing on a keyboard, and doors opening and closing.

We calculated the correlation values for each second of the audio signals and found a distribution which could be modeled with a Gaussian [7]. The states of being close or not (N_1 = {*close*}, N_2 = {¬ *close*}) and being in the box or not (B_1 = {*box*}, B_2 = {¬ *box*}) were defined to calculate the probability of being close given the correlation value of the audio signal:

$$p(N_1|corr) = \frac{p(corr|N_1) * p(N_1)}{p(corr)}$$

where $p(corr\,|\,N_1)$ can be written as $\sum_{B_i} p(corr\,|\,N_1,B_i)*p(B_i)$. The normalization factor $p(corr)$ can be extended to $\sum_{B_i}\sum_{N_j} p(corr\,|\,N_j, B_i)*p(N_j,B_i)$. Since N_j and B_i are independent, $p(N_j,B_i)$ can be written as $p(N_j)*p(B_i)$. The probability of being in the box $p(B_1)$ can be derived from the photo sensor. For the probability value of being close, we use the value from the evaluation of the last time step, therefore accumulating the probability over time.

Figure 3 shows the probability function plotted for our test data for different sampling rates of the audio signal. One evaluation of the probability function was calculated using the bias from the light sensor and one without it. The first 580 seconds the devices were together; after that, one of the devices was enclosed in a box, and after 920 seconds the devices were placed in two separate rooms. The probability function distinguishes the situations of being together or not reasonably well. When the audio signal is sampled at 8 kHz (left plot), the correlation values are rather high, regardless of whether the devices are in the box or not. However, in the case when the audio signal is sampled at 200 Hz (right plot), the light bias considerably helps to improve the overall performance. Since the computational cost for the correlation directly depends upon the sampling, this demonstrates that the light sensors can be used as supportive information for interpretation of the audio correlation.

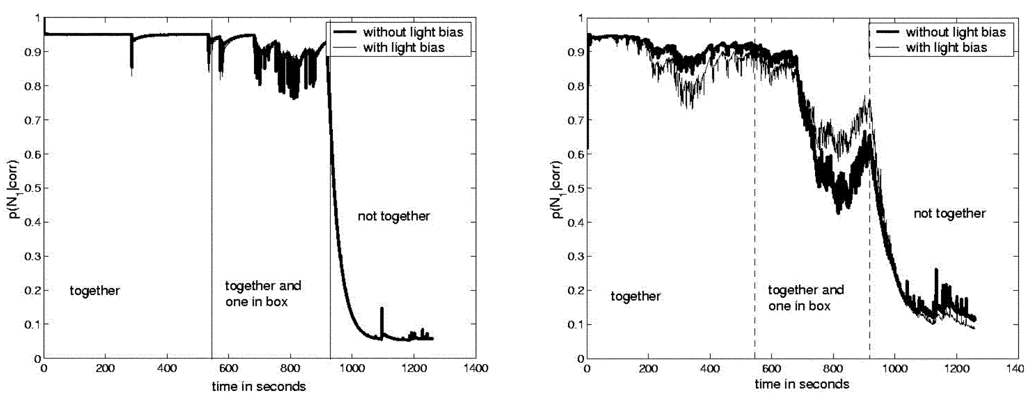

Fig. 3. Probability of proximity using the audio and photo sensor. The audio signal has been sampled at 8 kHz (left) and 200 Hz (right).

5. Conclusion and Future Work

Proximity measures are of great importance for situation-aware ubiquitous computing. This paper proposes a semantic proximity hierarchy based on a wireless sensor network. In particular, we argue that the proximity information gained through sensors is complementary to pure positional information. In future, we will also explore issues related to *ad hoc* sensor networks, where sensors and sensor configurations are not fixed, but different sensors might be coming and going. It is also of great interest to investigate how situation information is distributed in the network.

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