Intensity-based Object Localization and Tracking with Wireless Sensors*

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ABSTRACT

In this paper we present a first evaluation of an application of our intensity-based localization scheme in a real wireless sensor network. We implemented an object localization and tracking algorithm that solely depends on the values gathered by motion detectors. Based on this information and the positions of the observing sensors, the algorithm is not only able to track the position or trace of a moving object by considering the positions of the closest sensor(s) to the object, but is also able to estimate the location or path of the object. With our approach the location of a moving object can be estimated with minimal constraints on both the sensor hardware and the moving object what makes it a very lightweight approach. The applicability of our intensity-based localization algorithm is feasible even with the highly limited hardware implemented on existing sensor nodes.

1. INTRODUCTION

The main goal of this work is to prove the applicability of the intensity-based localization scheme ([12],[7]) on real existing hardware. In [12] we have shown that event localization solely based on the knowledge of the signal intensities measured on sensor nodes is mathematically possible. However we did not prove the applicability of the algorithm on real hardware in real physical environments with different physical properties of different types of signal propagation medium.

We therefore tested the applicability of our localization scheme on the ESB sensor boards from Scatterweb [10]. These sensor boards are equipped with a number of sensing devices, namely motion, temperature, vibration, light, and sound sensors. The development and research interest is thereby on miniaturization and low power operation of the sensor board hardware and is mainly focused on communication and operating system issues. Consequently, the implemented sensors are cheap and not intended to provide advanced sensing functionality.

While analyzing the usability of the individual sensors we encountered the problem that all implemented sensors are so inaccurate that the intensity determination of the sensed signals is not feasible. The sensors implemented on the ESB sensor boards are useful to decide whether there is an event or not, but not to determine the intensity of the event.

Being confronted with the sensing hardware constraints mentioned above we had to find an alternative way to determine the intensity of an event. We found a solution by sampling the sensors a certain number of times in a predefined interval. This solution leads to suitable results in particular when using the motion sensor. Due to these insights we can use the passive infrared sensor (PIR) to localize and track moving objects (humans).

The related work is discussed in section 2. A brief overview of the intensity-based localization algorithm and a short introduction to its mathematical principle is given in section 3. In section 4 we describe the hardware platform we use for our experiments. The results of these experiments are discussed in section 5. Conclusions and future work can be found in section 6.

2. RELATED WORK

In the last years a number of sensor network platforms have been proposed. The most popular platform is probably the Mica platform from Crossbow [4]. The Mica motes are equipped with some sensors that are however not useful in our context. The tmote sky sensor boards [8] are again not equipped with sensors that we could benefit from. The BTnode platform [2] is not at all equipped with sensors.

Object localization and tracking have been investigated in a number of approaches. The proposed schemes differ in the way they get range estimations and how they perform event observations. In [11] the distance of a sensor node to an event is approximated using the time of arrival (TOA) of the signals emitted by an event. The TOA values are routed together with the sensor node positions to a sink node, where the location of the event is computed as the maximum of a four-dimensional consistency function. In [13] a probabilistic localization algorithm is applied where sensors with high probabilities are queried by their responsible cluster heads to provide detailed information about a moving object. This approach operates fully distributed whereby the

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cluster heads are responsible to forward the information they collected to a base station or to share it with other cluster heads. In this approach the event location is not computed, but approximated by the position of the closest nodes that sense it. Sextant [5] uses Bézier regions to represent the possible locations of nodes as well as of events. Positive and negative network constraints are needed to build these Bézier regions. Consequently, these network constraints have to be distributed in the network. For the positioning a given number of landmarks are needed. A distributed algorithm for object tracking has been proposed by [1]. This approach supports event detection and tracking, but no event localization. A moving object is thereby tracked by a moving cluster of nodes, whereby the cluster leader dynamically changes.

Many existing localization algorithms ([11], [3]) depend on the possibility to distinguish two kinds of signals transmitted by an event. Thereby, the distance of the event is derived from the time difference of arrival (TDOA) of two different signals. For example, [11] uses the time difference of arrival between the shock wave and the muzzle blast generated by a gun to estimate the distance to the event. In many cases the dependency on two different kinds of signals is restrictive and not easy to fulfill. In contrast to these algorithms, the algorithm discussed in the next section depends only on the intensities derived at the sensor nodes. A similar algorithm was proposed in [7]. The sensor and hardware requirements of their application were however much different from ours.

3. INTENSITY-BASED LOCALIZATION

In ([12],[7]) it has been shown that multilateration-based ([6],[9]) localization without the need of distance estimations is possible. Instead of knowing the distance it is sufficient that a sensor node is able to derive a spatio-correlated value indicating the intensity of an event. In this section we will shortly give the mathematical background and motivation of our approach. Interested readers are referenced to [12].

We assume that the intensity ω_X derived at a sensor node X located at (x_x,x_y) is related to the distance d_X the sensor node is away from an event E located at (e_x,e_y). This relationship is formalized in the following relation:

$$\omega_X \sim \frac{1}{d_X^{\alpha}} \qquad , \alpha > 1 \tag{1}$$

The exponent α in (1) affects the degree of attenuation of the measured intensity in dependence of the distance to the source of the event.

It is crucial that the intensity cannot be used as a direct substitute of the distance in order to estimate the position of an event, but the ratio of the intensities measured on two sensor nodes is inverse proportional to the ratio of their distances to the event. To formulate this equation we additionally need the theorem of Pythagoras:

$$d_X^2 = (x_x - e_x)^2 + (x_y - e_y)^2 \tag{2}$$

From (2) and (1) we can derive the general equation to get the ratio of the intensities of two sensor nodes S and S':

$$\frac{(s_x - e_x)^2 + (s_y - e_y)^2}{(s'_x - e_x)^2 + (s'_y - e_y)^2} = \left(\frac{\omega_{S'}}{\omega_S}\right)^{\frac{2}{\alpha}} \tag{3}$$

In (3) you can see that the distance estimation normally needed by multilateration approaches is no longer used. (3) shows that the ratio of the distances from two sensor nodes S and S' to the event location is inverse proportional to the ratio of the intensities derived on both nodes. All possible locations of the event lay on a circle, unless the ratio is 1. This case will be discussed later. In the planar case we need at least three circles to get a unique intersection point of these circles. Obviously, the location of the event E is equivalent to that intersection point. This is true at least as long as the intensities derived at the sensor nodes are correct, an example generated with Maple is depicted in Figure 1.

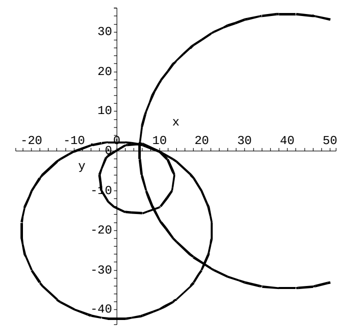

Figure 1: Event position as intersection of 3 circles.

In order to prove the applicability of (3), we have to show that the denominator cannot be zero. This is however trivial as from (3) we can conclude that the denominator can only become zero if $s'_x = e_x$ and $s'_y = e_y$. This means the location of the event is exactly at the position of sensor node S'. This case can be excluded, as the calculation of the position of an event is trivial if it occurs exactly at the location of a sensor node. In all other cases, the denominator cannot be zero.

If we assume that we have enough information to build at least three (in the planar case) instances of (3) a set of equations can be built that can be linearized and solved with a standard least-square approach: $E = (A^T A)^{-1} A^T b$. E is the location estimation of the event, A is the matrix containing the linear parts of the instances of (3) and b is a vector containing the constant parts of the instances of (3). When the inverse matrix cannot be calculated, the location cannot be computed and the multilateration fails. This happens if $\omega_S = \omega_{S'}$ what is the case if the ratio of the intensities is 1. This constitutes however no problem, as in this case the position of E lies on the vertical line through the middle of $\overline{SS'}$. The intersection of this vertical line with any of the participating circles results in the possible locations of event E. Consequently, in the case of $\omega_S = \omega_{S'}$ the matrix is not calculated and the location is estimated using the intersection of the vertical line with any two independent circles derived from the intensities.

4. HARDWARE PLATFORM

The sensor hardware we have used for our experiments is the ESB platform [10]. The nodes are built from standard components, consisting of a chip with a MSP430F149 microcontroller, 2kB of RAM, 60kB flash memory, and a low power consuming radio transceiver. Furthermore, the sensor boards are equipped with a number of sensors such as PIR, temperature, vibration, microphone, etc.

As already mentioned above we encountered a number of problems when trying to get scalar values indicating the intensity with which an event is sensed by the different sensors on a ESB sensor board. This is mainly due to the miniaturization of the implemented hardware. The sensors have to work with at most 3 V DC and should consume as little current as possible. Furthermore, the accuracy of the sensor reading may depend as in the case of the microphone on the input voltage, which varies over time.

Being confronted with such hardware constraints we decided to try to simulate the intensity by sampling the sensors a certain number of times in a predefined interval. When using the PIR sensor, this solution led to reasonable results. The idea of the procedure is that a moving object is more often observed by a close sensor board than by a sensor board which is farther away. This assumption seems to be reasonable as the trigger threshold of the PIR sensor is exceeded the quicker the closer the moving object is. This is obvious as in that case more infrared waves are received by the PIR sensor.

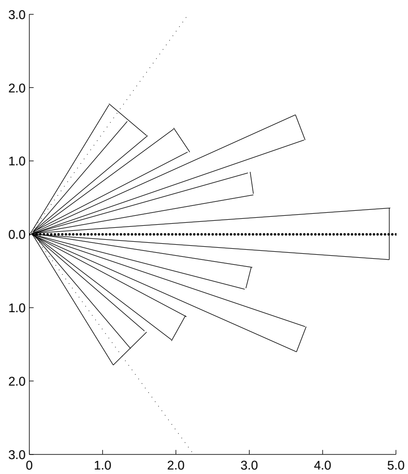

Figure 2: Horizontal detection area $[m^2]$ according to the PIR data sheet.

In Figure 2 the horizontal detection area of the PIR implemented on the ESB sensor boards is depicted. The vertical detection area of the PIR has a quite similar look. It is however not depicted as in all simulations we did, the observed object is positioned approximately on the same altitude as the sensor board. We have to add here that the horizontal area coverage of the PIR is not really satisfactory. The detection distance strongly depends on the angle of incidence and there are regions where even no detection is possible. This led to some limitations in our experiment setups that will be discussed in the next section. However, at the moment the PIR implemented on the ESB sensor boards is the only device we got feasible results with.

5. PERFORMANCE RESULTS

We will now discuss our experiment setups and the performance results we got with the different tests. As discussed in Section 4 we determine the intensity of an event sensed by a particular sensor board by sampling the sensor board a certain number of times in a predefined interval. To determine the interval as well as the number of samples in that interval we first had to determine the sample interval, i.e. the minimum time that is necessary to trigger the PIR sensor by measuring spectral differences of the infrared light while observing a moving object. By testing the PIR sensors we derived a value of approximately 130 milliseconds. Limited by this constant we set the measurement interval to two seconds and sampled the PIR sensor 15 times in that interval. The intensity of an event, which indicates the proximity to the event, i.e. of a moving object, is the number of times the event has been sensed within one interval, i.e. it lies between 0 and 15. It is important to keep in mind that the intensity is not sufficient to estimate the distance to the moving object (see section 3). But the intersection point of the circles derived from the ratios of the intensities is sufficient to estimate the location of the moving object. In order to observe a moving object for a certain amount of time we repeated the interval ten times in one test. This means, the observing period of a certain area was 20 seconds in each test. All listed values remain constant throughout all experiments.

In all experiments a loose time synchronization is needed. All sensor boards should measure the moving object approximately at the same time. As a test runs only for twenty seconds, clock drifts within that period can be neglected. The time synchronization is achieved by informing all ESB sensor boards to start their monitoring period at the same time, what is done by a broadcast message sent by the base station. After completion of the monitoring period, all ESB sensor boards respond with a message containing an array of the intensities measured during the monitoring period. With this data the base station has the necessary information to perform the intensity-based multilateration algorithm. The algorithm obviously considers only intensities sensed in the same sample period to estimate an object location. In the current state of our work we are mainly interested in the accuracy of the computed location and see therefore no restriction in performing the computation at the base station.

5.1 Localization of a Human Hand Moving at a Place

Our first experiment is somehow artificial, but we tried to minimize the influences of the PIR detection area distribution by minimizing the observing area of our sensor network. Consequently, we had to minimize the moving object as well. We placed eight sensors on a quadratic area with a dimension of 9 square meters. The setup of the experiment is depicted in Figure 3.

Figure 3: Experiment setup.

The sensors have been placed on a plain area where some holes have been provided, where the hand has been plugged through. Thus, the sensors observed only the hand. The rest of the body was hidden from the sensors. Positions and directions of the sensors are indicated by the black arrows depicted in Figure 4. The moving object (human hand) was located at the positions of the three large symbols (**o**, $+$, **x**) in the different runs. In this experiment we determined the intensity as the average of the intensities measured in one test, i.e. in 20 seconds. This has been done because the variations with the current PIR hardware is considerably in the individual intervals. Each experiment was repeated eight times at each location of the hand.

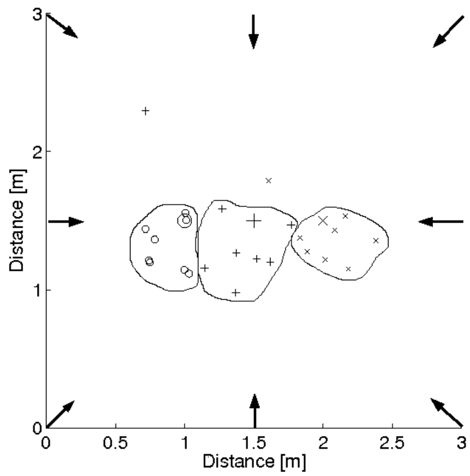

Figure 4: Localization of three different but close by positions of a human hand.

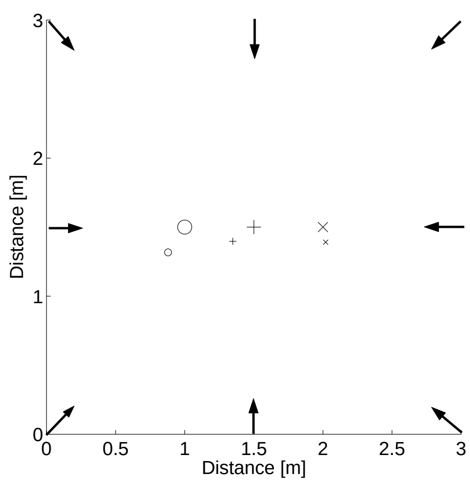

Figure 5: Barycenters of the clusters built by the position estimations.

The results of the first experiment are depicted in the Figures 4 and 5. In Figure 4 the individual location estimations of each experiment are shown, whereas the barycenters of the location estimations computed in each individual experiment are depicted in Figure 5. The distance errors of the barycenters are 0.22 m for o, 0.18 m for $+$, and 0.11 m for x. The results show that a spatial correlation of the real location and the estimated positions of the hand is given. The individual position estimations of the hand build more or less disjoint clusters around the correct hand locations. We think the results are quite promising, in particular when considering the small distances between the different hand locations and the detection properties of the current PIR sensors.

5.2 Localization of a Person Moving at a Place

In this second experiment we tried to localize a person moving with an approximately constant moving pattern at the same place. The person thereby moved at a speed of about $5\frac{km}{h}$. We placed ten ESB sensor boards in a corridor with five sensor boards on each side of the corridor. The sensor boards were placed 90 centimeters above the ground. Positions and directions of the sensor boards are again depicted as black arrows in Figure 6. The moving person was located at the positions of the three big symbols (**o**, **x**, $+$) in the different runs. The average of the intensities measured in one test was again used as the overall average during that test due to the same reasons as above. The estimation of the location of the person at a particular position was performed eight times.

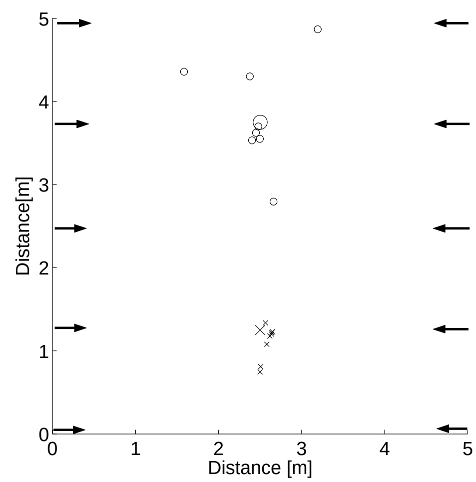

Figure 6: Location estimation of a person constantly moving at two places.

The results in 6 show again that a spatial correlation between the real location of the person and the estimated positions exists. The high variation of some estimations of location (**o**) compared to the results for location (**x**) are astonishing. We assume that the difference is founded by the varying lighting conditions in the room. Variations in the detection area distributions between the individual sensors could be another reason. What we wanted to show is however the spatial correlation between the estimations and the real location of the person. Due to the arrangement of the sensor boards in this experiment, the localization of an event is only adequate in one direction. Therefore, we identified variations for events that where not located close to the middle line. This impact is caused by the spatial detection distribution of the PIR sensors.

5.3 Tracking of a Moving Person

The first two experiments have shown that the localization of a moving object is possible as long as the sensors are deployed densely enough. In this last series of experiments we tried to track a person moving along a predefined path. Therefore we placed again ten ESB sensor boards in a corridor with five sensor boards on each side of the corridor. Due to the limited range of the PIR detection area we reduced the corridor width to four meters. The sensor boards were placed 90 centimeters above the ground. Positions and directions of the individual sensor boards are depicted in Figure 7. The person moved along a path which is indicated by the solid line. The person started in all runs at the left side of the corridor. Furthermore, the test person tried to move as constant as possible in all runs. As the person moves along the path during the observation period, the determination of the intensity as the averaged sensed intensity within one test run, as done in the experiments above, makes no sense. Instead we repeated each experiment eight times and took the average of the intensities determined in the according intervals of the individual runs. Thus we got ten location estimations for the path, one for each measurement interval.

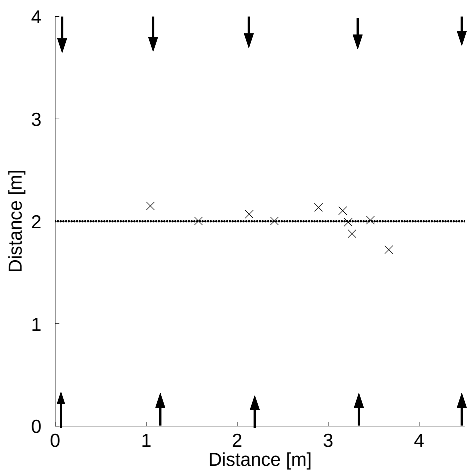

Figure 7: Tracking of a person moving along a path.

Figure 7 shows the results of the person tracking experiment. The location estimations effectively build a path, but the position estimations along the path are a little concentrated to the horizontal center of the corridor. This effect is due to the fact that there are no sensor boards placed further than the left and right borders. Consequently, as long as the moving object is close to the border its location estimation is shifted to the horizontal center as it is sensed by more nodes close to the horizontal center. This is not a property of the multilateration method, but of the sensing capabilities of the PIR sensors. Nevertheless, even with this restriction the localization and tracking of moving objects works as shown by the results we gained so far.

6. CONCLUSIONS AND FUTURE WORK

In this paper we have shown that an intensity-based localization on existing sensor boards is under certain restrictions possible. In particular the network density and the locations of the deployed sensor boards have a big influence at the localization accuracy and at the detection area where the localization is feasible. It is important to note that the goal of this work was not to present a final and operating tracking architecture, but to give a proof of applicability of our localization scheme. We have identified the sensing limitations of the current sensors implemented on the ESB sensor boards and proposed a solution for the PIR sensor. By using this PIR sensor we were able to measure the intensity of a moving object on the sensor boards. We have shown that a location estimation by using solely passive information and without the need of distance estimations is not only theoretically, but also in practice possible.

On the other hand we note that with the PIR sensors currently implemented on the sensor boards accurate localization in advanced applications is only restricted practicable. Nevertheless, we think that an intensity-based localization with more appropriate hardware would be promising. Another issue that could improve a real application of our approach is hardware calibration.

In our future work we will look for sensors which are capable of measuring real scalar intensities. We will also consider other sensors like microphones. Obviously with microphones and other sensors that depend on signal transmissions we will have to deal with reflections, directions, and so on that introduce a number of new difficulties. We will have to investigate the tracking of concurrently moving objects, what has not yet been considered as it does rather depend on classification techniques than on the exact event location prediction investigated in this work.

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