Calculation of the User-Direction in an Always Best Positioned Mobile Localization System

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ABSTRACT

In an Always Best Positioned (ABP) localization system the output of different localization techniques are fused together to get an even better position accuracy. Besides the information about the position of a user, his viewing or walking direction is also important. This paper describes an extension of our mobile APB system that uses RFID tags and infrared beacons. We describe how different direction information – derived from different sensors or calculations – can be fused together with the help of Dynamic Bayesian networks.

Keywords

Indoor Localization, Dynamic Bayesian Networks, Mobile Systems

1. INTRODUCTION

There is a vast amount of different localization techniques available. GPS is the most popular one for outdoor positioning. Although there are some hints that GPS can also be used for indoor localization [4] different techniques are favored for indoor scenario. These techniques often rely on senders like WiFi-access-points [1], infrared beacons [3], RFID tags [5] or ultrasound tags [6, 7]. The Always Best Positioned (ABP) paradigm tries to always determine the current position of a user by using the localization technique that is available at a given position, if there is only one technique available. If there are several techniques available it tries to combine (or fuse) these techniques (or their outputs) to get an even better result. In [2] we describe such an ABP system that uses infrared beacons and active RFID tags and that combines both sender types with the help of geo referenced dynamic Bayesian Networks. Besides the information about the position of a user, the information about her walking or seeing direction can also be valuable. A common example is an electronic museum guide that not



Figure 1: iPAQ PDA running the ABP localization system and with attached RFID reader.

only needs to know where the visitor is standing but also which exhibit she is currently looking at so the system can give the respective explanations. This paper is an extension to [2] and we will describe how the direction information from both sensor types (infrared and active RFID) can be fused together, again with the help of a dynamic Bayesian Network.

The rest of the paper is organized as follows: First we will give a short summary of our ABP system. Then the different sender types and how the direction information can be computed for each type will be explained. Section 3 is the main part and describes how the direction information can be fused together with a simple dynamic Bayesian Network and how the data has to be pre- and post-processed. An example calculation will be presented in section 4. We will conclude with a summary and an outlook on our future research.

1.1 The ABP System

This section summarizes the used ABP localization system. A detailed description can be found in [2]. The whole system runs on an iPAQ PDA (see Figure 1, left). As mentioned in the introduction, the system uses infrared beacons and active RFID tags. These tags and beacons are installed in the environment and the respective sensors are attached to the PDA (the built-in infrared sensor and an additional RFID reader card, see Figure 1, right).



Figure 2: Infrared beacon (left) and active RFID tag (right).

In our approach, we use dynamic Bayesian Networks (DBNs) to estimate the user position. The idea is as follows: Different types of senders have different characteristics. Active RFID tags have a radial emission whereas infrared beacons have a conical emission. Due to reflections and other physical factors that affect the radio signal, receiving RFID tags gives only weak evidence that a user is in the vicinity of the tags. In contrast, receiving an infrared beacon gives a strong evidence that the user is standing in front of the respective beacon. We designed a DBN that models these aspects.

If the sensors detect RFID tags and/or an infrared beacon, the System either creates instances of the DBN for each measured sender and associates them with geo coordinates (that are stored in the RFID tags) or, if there is already an instantiated network for a sensor, it updates the respective network. We call these DBNs geo referenced DBNs (geoDBNs). Every network that provides a belief above a certain threshold is used to calculate the current position of the user. This is done with a weighted combination of the geo coordinates, where the weights are proportional to the believe of each geoDBN:

$$UserPos_t = \sum_{i=1}^{n} \alpha \ w(\text{GeoDBN}[i]) \ \text{Coord}(\text{GeoDBN}[i]).$$

Here, n is the number of DBNs at time t, Coord(GeoDBN[i]) is the coordinate and w(GeoDBN[i]) the weight of the *i*th geoDBN. α is a normalization factor that ensures that the sum of all weights multiplied with α is one.

2. DIRECTION CALCULATIONS

This section describes the two different sender types that we use in our system and how the direction information can be extracted from each of them.

2.1 Infrared beacons

We use infrared beacons that are manufactured by eyeled $GmbH^1$ (see Figure 2, left). These beacons are powered by batteries and send out a 16-bit wide identification code that can individually be adjusted for each beacon. The emitted infrared beam has a range of about 6 meters and has, due to the physical attributes of light, a conical sending characteristic. The infrared beam can be read and decoded by standard infrared sensors as they are often integrated in PDAs, notebooks or mobile phones.

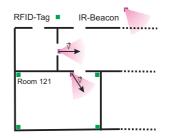


Figure 3: Part of room plan with direction vectors of two IR beacons.

2.1.1 Estimation of direction

Because the infrared beam is highly directional, the calculation of the walking direction is fairly easy. If the beacon sends its light in direction vector \vec{v} (see Figure 3) and the user receives the beacon then she is walking in direction $d\vec{r}_{IR} = -\vec{v}$. Of course this is only an estimation since the user can be slightly to the left or right of the main direction \vec{v} due to the conical sending characteristic. Also note that it is sufficient to use a two dimensional vector (the projection of the three dimensional direction vector – that includes the tilt of the beacon – on the x-z-plane).

2.2 Active RFID tags

Radio Frequency IDentification (RFID) tags are available as passive and active parts. In both forms, the tags are hard coded with an identification code that can be read out with a special RFID reader that sends out a radio signal. The passive tags get their power out of the reader's radio signal and therefore have a very low range. Active RFID tags have their own power supply through a battery. We use active RFID tags from Identec Solutions AG^2 (see Figure 2, right), which have a range of up to 10 meters. Due to the physical attributes of radio waves, the sending characteristic is radial. The reading devices for active RFID tags come in various form factors. In conjunction with the PDA, we use a PCMCIA reader card that is attached via an expansion pack.

2.2.1 Estimation of direction

Due to the radial sending characteristics the estimation of the direction is not as easy as with the infrared beacons. We estimate the direction as follows: Store the starting position P_0 of the user in a variable *lastPosition*. With every new calculated position P_n calculate the distance to *lastPosition*. If the distance is large enough (a few meters), calculate the direction vector $dir_{diff} = lastPosition - P_n$ and store P_n in *lastPosition*. Repeat the last two steps with every new calculated position.

2.3 Discussion

The direction estimation with infrared beacons is rather accurate but the beacons are not always in reach of the user. The direction estimation through difference calculation is always possible (whether there are only RFID tags available or only infrared beacons or both) but it is also inaccurate . A combination of both techniques with a dynamic Bayesian Network should give better and more stable results.

¹http://www.eyeled.de

²http://www.identecsolutions.com

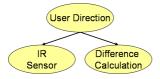


Figure 4: Dynamic Bayesian Network for direction fusion.

3. FUSION OF THE RESULTS

In this section we describe how the directional information from the infrared beacons and RFID tags can be combined.

As described in the introduction we use a dynamic Bayesian Network to fuse the direction data. The network itself is rather simple (see Figure 4): It contains only three nodes and each node contains evidences for direction north, south, east and west. The topmost node is the user direction node. This is the node that will contain the calculated (combined) direction after the roll-up and inference routines have been calculated.

The lower left node is the node for the infrared based direction vector. As explained above, the estimated direction $d\vec{r}_{IR}$ is slightly inaccurate because the user can stand to the left or right of the main sending direction \vec{v} . This fact is encoded in the conditional probability table (CPT) of the infrared node: The probability that the user is heading in the estimated direction $d\vec{r}_{IR}$ is set to 0.9, the probability that she has a variation perpendicular to $d\vec{r}_{IR}$ is set to 0.045 (in both directions) and the probability that she is walking backwards ($-d\vec{r}_{IR}$) is set to 0.01.

The right hand node is the node for the direction that was calculated through the difference of two points (dir_{diff}) . Due to the fact that this direction is rather inaccurate the CPT entries are as follows: 0.65 for heading exactly in direction dir_{diff} , 0.15 for the variance perpendicular to dir_{diff} and 0.05 for walking backwards.

3.1 Decomposition of a Direction Vector into Evidence Values

We need a way to represent an arbitrary direction vector as evidence values, so we can insert the estimated directions $d\vec{r}_{IR}$ and $d\vec{r}_{diff}$ in the respective nodes of the DBN. We do this by decomposing it in its x-component X and its y-component Y (see Figure 5, left) and by making sure that the sum of the derived evidences is one: If Y > 0 (this means the user has a north component in her direction) the evidence for north e(north) is set to $\frac{Y^2}{X^2+Y^2}$ and the evidence for south e(south) is set to zero. If Y < 0 (the user has a south component in her direction) it is vice versa: $e(north) = 0, e(south) = \frac{Y^2}{X^2+Y^2}$.

The same principle applies for the x-component: If X > 0(direction has east component) then $e(east) = \frac{X^2}{X^2+Y^2}$ and e(west) = 0. If X < 0 (direction has west component) then $e(west) = \frac{X^2}{X^2+Y^2}$ and e(east) = 0.

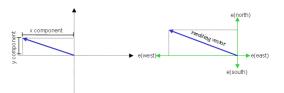


Figure 5: Decomposition and composition of direction vector.

Note that the sum of the evidences is always $\frac{X^2}{X^2+Y^2} + \frac{Y^2}{X^2+Y^2} = \frac{X^2+Y^2}{X^2+Y^2} = 1.$

3.2 Composition of a Direction Vector out of Evidence Values

The estimated directions $di\vec{r}_{IR}$ and $di\vec{r}_{diff}$ are decomposed as described above and the resulting evidences are inserted into the lower nodes of the DBN for each time slice (one time slice is added for every new measurement of the localization system). After performing the roll-up and the inference procedures of the DBN, the user direction node will contain evidences for north-, south-, east- and west-components of the new direction. These evidence values must be combined to get a new direction vector. We do this by treating the components as a parallelogram of forces (as known from physics, see Figure 5, right). The new direction vector dir_{res} consists of the x-component X = e(east) - e(west) and the y-component Y = e(north) - e(south) of the new calculated evidence values. The length of the calculated direction vector dir_{res} can be used as a confidence value (e.g. the longer the vector the higher the confidence that the computed direction is correct).

4. EXAMPLE CALCULATION

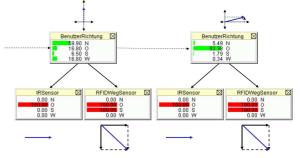


Figure 6: Example calculation showing two time slices.

Figure 6 shows an example calculation. The top left node shows the result of the previous time slice, above it the composition of the calculated direction vector can be seen. Note that the evidence values for east and west are exactly the same, while the evidence for north is much bigger than for south. This causes the resulting vector to point strictly north. The two nodes below show the new evidences of the current measurement. The infrared direction has 100% evidence for east (the vector can be seen below the node), the difference direction node has the same evidence value for east and south. The network on the left side of Figure 6 shows the result after the inference routines have been carried out. The top node has strong evidence for east and still little evidence for north. This is because both direction nodes give evidence for east but only the (inaccurate) difference direction node gives evidence for south. Because the DBN includes the previous calculated direction, the north component is still present in the new direction. This is the expected result of such a system, because it helps to smooth out fast jumping of the direction information and it emphasizes the direction for which is has the most evidence.

5. CONCLUSIONS AND FUTURE WORK

This paper gave an idea how to combine direction information resulting from different sensor-types or from different calculation approaches with the help of dynamic Bayesian Networks. We have shown how such a DBN can be constructed, how the direction vectors can be decomposed into evidence values and how a new direction vector can be constructed from calculated evidence values.

First tests of our implementation gave us the impression that the combined direction is much more accurate and much more stable than the direction derived from the infrared beacons or from the difference method alone. This seems due to the fact that the DBN includes the previously calculated direction (from the previous time slice) into the next calculation and because it weights the two original direction differently (according to their precision). At the moment we are working on a benchmark suite to measure the accuracy of our position- and the here described direction-calculation.

6. ACKNOWLEDGMENTS

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7. REFERENCES

- P. Bahl and V. N. Padmanabhan. RADAR: An In-Building RF-Based User Location and Tracking System. In *INFOCOM (2)*, pages 775–784, 2000.
- [2] B. Brandherm and T. Schwartz. Geo Referenced Dynamic Bayesian Networks for User Positioning on Mobile Systems. In T. Strang and C. Linnhoff-Popien, editors, *Proceedings of the International Workshop on Location- and Context-Awareness (LoCA), LNCS 3479*, pages 223–234, Munich, Germany, 2005. Springer-Verlag Berlin Heidelberg.
- [3] A. Butz, J. Baus, and A. Krüger. Augmenting Buildings with Infrared Information. In Proceedings of the International Symposium on Augmented Reality(ISAR). IEEE Computer Society Press, 2000.
- [4] B. Eissfeller, A. Teuber, and P. Zucker. Untersuchungen zum GPS-Satellitenempfang in Gebäuden (german). AVN Allgemeine Vermessungsnachrichten, (4), April 2005.

- [5] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil. LANDMARC: Indoor Location Sensing Using Active RFID. In *IEEE International Conference in Pervasive* Computing and Communications 2003 (Percom 2003), 2003.
- [6] Ubisense Unlimited. Ubisense. http://www.ubisense.net.
- [7] R. Want, A. Hopper, V. Falcao, and J. Gibbons. The Active Badge Location System. ACM Transanctions on Information Systems, 10(1):91–102, January 1992.