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Indoor positioning of metal parts by fingerprinting using passive RFID

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Abstract

In a smart factory, location-aware functions are an important feature. An asset's position provides the context for making decisions in the factory. In this study, we have proposed a technique for positioning metal parts using a passive RFID (Radio-frequency identification) system. We applied the fingerprinting method using RSSI (Received Signal Strength Indicator) values of the tag to estimate its position. The position was estimated with an accuracy of 89% in an area of 3.6x3.6 m. This provides a potentially more affordable means of tracking metal parts in a factory, with acceptable accuracy at lower costs than other indoor positioning techniques.

Keywords: Indoor positioning; Indoor localisation; RFID; RSSI; Euclidean distance

1. Introduction

As factories are getting ready to join the fourth Industrial revolution, there is a strong wave of development of intelligent manufacturing systems supported by an abundance of sensors, the resultant explosion of data, and the availability of computing resources to utilize this data. A key feature of an intelligent manufacturing system is context-aware computing, where physical position is one of the major contextual attributes. For a machine to provide intelligent assistance, it must understand our real-world context [1].

A distinguishing feature of location-aware systems is that the information and/or interface presented to the user is a function of his/her physical location [2]. Apart from the user's location, the interface can be a function of the location of some other assets, like raw materials, waste by-products, consumables, parts, hand tools and material handling systems. Continuous tracking of such assets can enable us to deliver location-aware services in industrial applications. Another benefit of automated asset tracking is the high visibility of individual items, leading to real-time inventory management. Tracking of such assets is not new, but the technologies used for tracking are evolving. For many years, bar codes have been used to track inventory as it provides an inexpensive and simple method. However, using bar codes requires manual intervention, which makes it error-prone and time consuming, particularly at a large scale. A better option is to implement an indoor positioning system.

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An indoor positioning system (IPS) continuously determines the position of a person or an object in an indoor environment. It can be achieved by various ways, which have been compared in some surveys [3–6]. Al-Ammar et al. elaborated some performance metrics for indoor positioning systems, which can be used as criteria for selecting the most suitable technology for the purpose [5]. For us, the task was to track metal parts around an assembly station at an affordable cost. For this, we chose an UHF (ultra-high frequency) passive RFID (Radio-frequency identification) system. Even within passive RFID, the choice of measured parameters depends on the hardware used. Some studies have used RSSI (Received Signal Strength Indicator), some have used Angle of Arrival, while others have used other parameters such as phase difference and read count. In our case, we used RSSI for its reliability at low cost. We also tried to find a correlation between read count and distance, but our preliminary studies did not yield any conclusive relationship. Passive RFID systems come with some drawbacks like attenuation, occurrence of energy null zones, tag and antenna collision, cross paths of signals and interference from other Radio-frequency devices [7–9]. However, there are ways to deal with some of these problems, and such systems have been used in many studies with reasonable success.

Ting et al. studied the feasibility of using passive RFID tags for indoor positioning [10]. Initially they studied the read rate of tag as a function of distance from the antenna. Then they generated a look-up table against which they compared other datasets to estimate the location of the tag. Their experimental area was a square of 3m x 3m, which was divided into a grid of nine cells. They estimated the correct cell with 93% accuracy, but the cell size of 1m x 1m was too large for that area, which makes the results less impressive. Bouchard et al. presented a passive RFID localisation technique using Trilateration from RSSI values [11]. In an experimental area of 6 sq. m, they could estimate the location with an error of 14cm. Dao et al. presented a localisation system using UHF RFID passive tags [12]. On a table of 180cm x 90cm, they could estimate the location with an error of 32.3cm. From these studies, we realized the need for improving accuracy of positioning for larger areas at affordable cost.

2. Methods

For this study, we used an RFID system from Zebra consisting of four antennas connected to one reader. The model of the reader was FX7500 and the model of antennas was AN480. The tags, made by 3M, were designed to be attached to metal objects. The area was a square of 3.6m x 3.6m with antennas at each corner, but the tags were placed in a square of 2.4m x 2.4m concentric to that area. The antennas and tags were all held at a height of 1m from the floor. The antennas were labelled from A1 to A4, kept in cyclic order, with A4 at the origin [0,0] and A1 at [3.6,0]. All antennas faced towards the centre of the square, as shown in fig1.

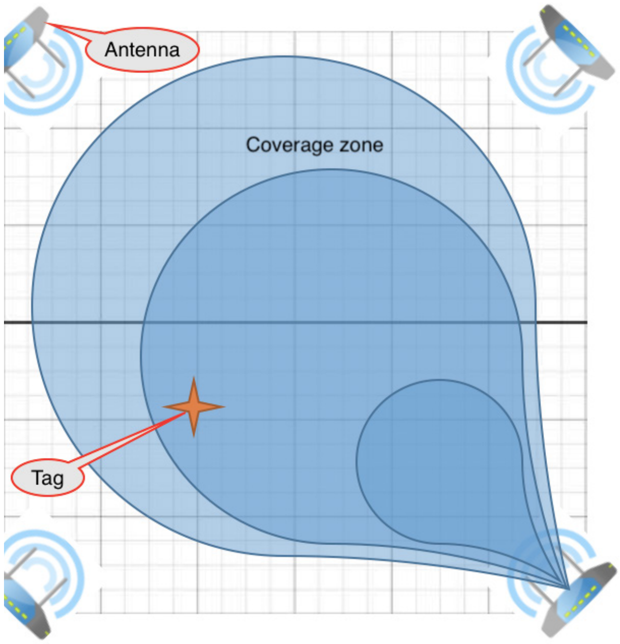

Fig. 1. Top view of the experimental setup. Three zones are shown for one of the antennas as per their received signal strength.

In this study, we have employed an RSSI-based fingerprinting method [13]. Initially, the object tag is placed in a particular direction at each of the 25 grid points starting from (0.6,0.6) and ending at (3.0,3.0). The RSSI values of the tag from each antenna are collected at each of these locations. This dataset is taken as the reference table, which can be seen as the RSSI fingerprint or radio-map of the area. The other datasets are compared with the reference table to estimate the location of the tag. For estimation, we applied the weighted kNN (k-Nearest Neighbours) technique [14].

3. Results

The zone of influence of an antenna is roughly the shape of a lobe, but it cannot be calibrated for reference because of frequent variations in the environment. Location fingerprinting with multiple antennas is a proven technique as shown in literature [15]. Initially, we applied this technique with the tags facing the negative y direction. Out of two datasets collected on a particular day, one was taken as the fingerprint and the other was used to estimate the location of the tag. In this experiment, we estimated the location with an average error of 6cm, as shown in fig2. However, using datasets taken on other days, the average error went up to 25cm.

The localisation error for other directions based on radio-map in one particular direction was very high. Therefore, we decided to take the radio map in all four directions in the plane. Using these radio maps, we could estimate not only the location but also the orientation of the tag after taking data from different days. Thus, we could turn the challenge of varying orientation into an advantage. As per Table 1, 23 out of 25 estimates in the positive x direction were correct, which means 92% accuracy in this direction. For all four directions taken together, the average accuracy was 89%.

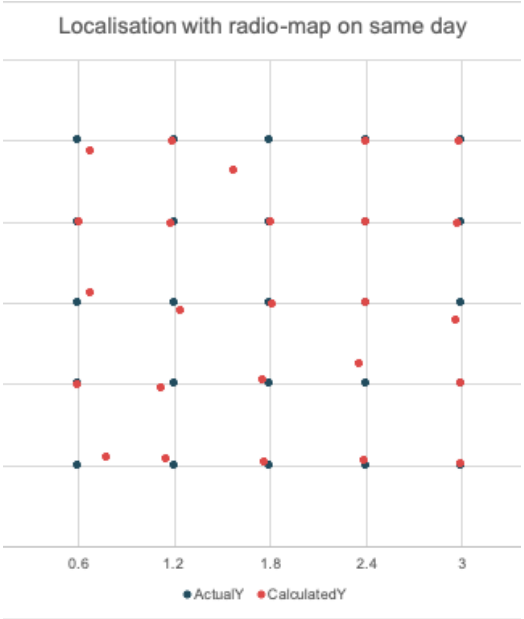

Fig 2: Actual and estimated locations of the tag on the grid.

During the experiments, there were certain positions where the one of the four antennas did not read the tag. This happened in about 5% of all readings, which we presume was due to the occurrence of null spots. In such cases, we moved the tag by 5cm in a direction favourable to the concerned antenna, without changing its orientation.

4. Discussion

Every tag performed differently. Although the difference was little, it was significant enough to show large errors in the estimated locations. Therefore, using the RSSI values of reference tags to interpolate the location of the object tag is not advisable.

Since there is a logarithmic relationship between the distance of the tag from the antenna and the RSSI value received by the antenna, the accuracy of estimation decreases with distance. It remains to be seen how accurate the estimations in a larger area are.

Table 1: Readings in positive x direction from the dataset

Actual X	Actual Y	Actual Dir	N1 x	N1 y	Dir 1	N2 x	N2 y	Dir 2	N3 x	N3 y	Dir 3	N4 x	N4 y	Dir 4
0.6	0.6	+X	0.6	0.6	+X	0.6	0.6	Y	2.4	0.6	-X	0.6	1.2	Y
0.6	1.2	+X	0.6	1.2	+X	1.8	3	-Y	2.4	1.8	-X	1.2	3	Y
0.6	1.8	+X	0.6	1.8	+X	1.8	3	-X	1.8	2.4	-X	0.6	1.2	+X
0.6	2.4	+X	0.6	2.4	+X	0.6	3	Y	1.2	2.4	+X	0.6	2.4	Y
0.6	3	+X	0.6	3	-Y	0.6	3	Y	0.6	3	-X	0.6	3	+X
1.2	0.6	+X	1.2	0.6	+X	1.2	1.8	Y	0.6	2.4	-Y	2.4	0.6	-X
1.2	1.2	+X	1.2	1.2	+X	1.2	1.8	+X	1.2	2.4	Y	0.6	2.4	-Y
1.2	1.8	+X	1.2	1.8	+X	2.4	2.4	-X	1.8	2.4	+X	1.2	1.2	+X
1.2	2.4	+X	1.2	2.4	+X	2.4	2.4	-X	1.2	1.8	+X	0.6	3	Y
1.2	3	+X	1.2	3	+X	0.6	2.4	-X	1.8	3	-X	0.6	3	+X
1.8	0.6	+X	1.8	0.6	+X	1.8	2.4	-Y	1.2	0.6	Y	1.8	1.2	Y
1.8	1.2	+X	1.8	1.2	+X	1.8	2.4	+X	1.2	2.4	Y	1.2	1.8	+X
1.8	1.8	+X	1.8	1.8	+X	1.2	1.8	+X	2.4	2.4	-X	1.2	2.4	Y
1.8	2.4	+X	1.8	2.4	+X	2.4	1.8	+X	1.8	3	+X	2.4	2.4	-X
1.8	3	+X	1.8	3	+X	2.4	1.8	+X	1.2	2.4	+X	2.4	3	-X
2.4	0.6	+X	2.4	0.6	+X	1.8	1.8	Y	2.4	1.8	-Y	1.8	1.2	Y
2.4	1.2	+X	2.4	1.2	+X	2.4	2.4	Y	1.8	2.4	Y	3	2.4	-Y
2.4	1.8	+X	2.4	1.8	+X	1.8	2.4	+X	1.2	1.8	+X	2.4	2.4	-X
2.4	2.4	+X	2.4	2.4	+X	3	2.4	+X	3	2.4	-X	1.8	3	Y
2.4	3	+X	3	3	-X	2.4	3	+X	2.4	3	Y	3	1.8	+X
3	0.6	+X	3	0.6	+X	3	1.2	Y	2.4	0.6	Y	2.4	3	-Y
3	1.2	+X	3	1.2	+X	1.8	2.4	Y	2.4	1.8	Y	1.8	3	Y
3	1.8	+X	3	1.8	+X	3	2.4	Y	3	3	-Y	2.4	3	Y
3	2.4	+X	3	2.4	+X	3	3	-X	2.4	2.4	+X	3	1.8	+X
3	3	+X	3	3	+X	3	3	Y	3	3	-X	2.4	3	+X
Estimates					23			1			0			1

The experiments were conducted over a period of several weeks. For every experiment we had to set up the antennas and remove them after taking the readings. Although the antennas were placed in the same position and orientation, even slight variations in their placement affected the outcome. We believe that if the antennas and their orientation were fixed throughout the experiments, we would get better and more reproducible results.

5. Conclusions and future work

Since we also estimated the orientation of the tags apart from their location, it is more apt to call this positioning instead of localisation. This appears to have been the first study involving positioning of metal parts in a manufacturing assembly facility. Another claim of this study is affordability compared to other technologies. As per the quotations we received, an Ultra-Wide Band (UWB) system that claims to deliver similar accuracy over the same area costs about four times more than that of our Passive UHF RFID system. Moreover, the tags of an UWB system cost much more than passive RFID tags, which leads to higher costs in scaling up.

When applied as a context, the position of a tag can tell whether the part is properly oriented during the assembly process. The antennas are planned to be installed around an experimental assembly station, which would be a part of a smart factory R&D platform. In future, this approach is planned to be extended to 3D spaces. We also need to speed up the switching between antennas to estimate the location in real-time (RTLS). The variation among tags is another problem. Any radio-map will be valid for a particular tag, but in real scenarios we need to locate several different tags, whose characteristics are likely to be different. One way of dealing with this issue could be to reuse a fewer number of tags and benchmark them against each other.

On the analytics side, we need to devise a technique that employs machine learning to vary the radio-map as per the RSSI values of the reference tags. Ultimately, we plan to integrate the localisation system with a 'Smart factory' dashboard to implement and support context-aware decision-making in the factory.

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