Characterising Indoor Positioning Estimation Using Experimental Data from an Active RFID-based Real Time Location System

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Indoor positioning has attracted much research effort due to many potential applications such as human or object tracking, and inventory management. Whilst there are a number of indoor positioning techniques and algorithms developed to improve positioning estimation, there is still no systematic way to characterise the estimation. In this paper, we propose a method comprising of 3 characteristics to characterise indoor positioning estimation. We conducted experiments on an active Radio Frequency Identification (RFID)-based Real Time Location System (RTLS) in different environmental conditions. We used both a human and a robot to traverse two experimental areas and collected positioning results at different fixed points along the traversal path. Using this basic positioning data, we were able to characterise positioning estimation using 3 characterisations: position accuracy, centroid consistency, and angular distribution. We demonstrate the use of these characteristics for examining different points in a travelling path and different measurements.

Keywords: Real Time Location System (RTLS); Radio Frequency Identification (RFID); Indoor Positioning Estimation.

1. Introduction

Indoor positioning refers to techniques and algorithms that can estimate objects' position inside indoor environments. Accurate indoor positioning systems offer a number of benefits for various applications, including human or object tracking, indoor navigation, etc. Various indoor positioning systems have been developed using different technologies such as WLAN (Bahl and Padmanabhan (2000); Laoudias, Michaelides, and Panayiotou (2012)), Bluetooth (Tadlys Wireless Communications Ltd. (2014); Kotanen et al. (2003)), camera imaging (Sugimoto et al. (2014); Krumm et al. (2000)), etc.

Current indoor positioning research focuses on deviations between positioning results and their true position, *positioning errors*, as a means to gauge positioning performance (Adler et al. (2015)). For example, works such as (Hazas and Hopper (2006); Casas et al. (2006); Ruiz et al. (2012); Adler, Schmitt, and Kyas (2014)) utilise mean error, mean square error or positioning error, as measures to report accuracy, while research such as (Mirowski et al. (2012); Ni et al. (2004); Saad et al. (2012)) adopts cumulative distribution function (in the forms of percentiles of error) for the same purpose. While positioning error reflects how truthful positioning results are with respect to the true position and hence, a useful measure of positioning performance, it cannot convey other characteristics such as whether

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the positioning results are converging or diverging, or if the estimation is biased in some ways in different areas. These characteristics are also important in articulating positioning performance since they reflect how well the system performs under different conditions. Furthermore, if we are able to characterise positioning estimation of a system, we have a basis to estimate and predict the likely result of that system; the knowledge of positioning estimation characteristics can be useful in supporting positioning estimation. However, positioning characterisation has not been established.

In this work, we conducted multiple experiments with an active RFID-based Real Time Location System (RTLS), using both human and the NAO robot[1]. NAO is a humanoid robot that can perform various and advanced operations. The experiments were conducted in two indoor locations: one at the warehouse of Adilam Technologies[2], the other at an university laboratory. The system works by measuring the ranges from one (or more) RFID tags, worn by a tracked object, to multiple RFID readers placed within a monitored area, and using multi-lateration to estimate the positions of the tag(s). Though we used a positioning system that is based on radio frequency (RF) signal in our experiments, we do not focus on studying the impact of human tissues on RF signal propagation, which has attracted many research works such as (Bancroft et al. (2012); Garcia-Villalonga and Perez-Navarro (2015)).

Based on these experiments, we have developed a new method for characterising indoor positioning estimation. We propose three characteristics for such positioning estimation: (a) the position accuracy with respect to the true position, (b) the centroid consistency among positioning results, and (c) the angular distribution of positioning results with respect to the true position. We also propose corresponding metrics suitable to be used to report these characteristics.

The key new contributions of our work are thus:

- design of experimental platforms to systematically and repeatably measure positioning accuracy, demonstrated in two different indoor environments with two different platforms;
- the introduction of centroid consistency and angular distribution to characterise accuracy;
- systematically characterising an indoor positioning estimation using position accuracy, centroid consistency, and angular distribution characteristics. We show in our experiments how these new characteristics can be used to compare positioning estimations of different positioning systems.

We present the motivation of our work in Section 2. We review various methods to report positioning results of a system in Section 3. We present our characterisation method in Section 4. We present our experiments, and the results of applying our characterisation method in Section 5. We discuss the meaning and implication of the proposed estimation characteristics in Section 6. We present the threats to validity of our work in Section 7. We conclude the paper and discuss possible future works in Section 8.

[1]http://www.aldebaran.com/en
[2]http://www.adilamtech.com.au/

2. Motivation

Consider an elderly care environment where equipment, medical personnel and elderly patients need to be tracked. An accurate positioning system would allow for better monitoring of available personnel to respond to emergencies (or even simply improved staff allocation to non-emergency tasks); tracking of equipment and consumables to improve both logistics for equipment management, but more importantly to ensure a safe living environment for mobility-limited patients; and monitoring of patients' safety, in terms of their general location in the facility but more importantly their specific location and historic location in rooms (to proactively determine potential injury or illness).

To achieve these goals, an effective indoor positioning system is required to provide a high degree of positioning accuracy. Our first aim is to understand and characterise the positioning estimation by conducting multiple experiments with an active RFID system. The active RFID system was motivated by the need for a moderate-to-low cost, high volume, high degree of accuracy, and ability to retrofit existing spaces without expensive modifications. Each person or thing in the environment to be tracked will utilise a single active RFID tag. A collection of RFID readers will be used to determine indoor position to a high degree of accuracy.

Key research questions we wanted to answer include:

- How do we characterise indoor positioning estimation?
- How accurately can the position of one active RFID tag be determined using multiple readers?
- How can we apply these results to characterising the accuracy of indoor positioning system in general?

3. Related Work

Positioning results have typically been reported in terms of the mean error, and the cumulative distribution function (CDF) of the error. The error is computed as the distance from a positioning result to the true position, while the CDF is usually reported in terms of percentiles of the errors. For example, an integration of WiFi and Inertial Navigation Systems (INS) for indoor positioning has been proposed (Evennou and Marx (2006)). The results of this work show that fusing the INS information in a WiFi (WLAN) system using particle filter can result in a mean error of 1.53 metres, which is smaller than that of the RADAR system (Bahl and Padmanabhan (2000)), being 3.88 metres. The LANDMARC system (Ni et al. (2004)) uses RFID technology to compute people's location inside building. It first identifies the closeness of the tracked tag to a number of reference tags, and then uses the position of these reference tags to estimate the location of the tracked tag. The experimental results show that the number of reference tags that can yield the most accurate positioning result is 4, with 50 percentile having an error distance of around 1 metre. It is better than the RADAR system (Bahl and Padmanabhan (2000)), whose 50 percentile is around 2.37-2.65 metres.

Other research, such as (Casas et al. (2006); Hazas and Hopper (2006); Jin, Soh, and Wong (2010)), reports positioning results in terms of mean error and confidence interval of the mean. For example, a robust least-median-of-squares method to mitigate the NLOS issue in indoor environment has been proposed (Hazas and Hopper (2006)), where a tag's position is calculated based on the time of flight measurements of ultrasonic signals emitted from several beacons. It was reported that 99th percent confidence interval of 2D positioning error of ± 3 cm has been obtained, after 750 localizations with at least 4 beacons that are under direct vision in the experimental area. Other metrics such as mean-square-error (MSE), root-mean-square (RMS) and percentage of positioning error with respect to the total travel distance have also been used. For example, an indoor navigation system based on foot-mounted inertial measuring units and RFID measurements has been proposed (Ruiz et al. (2012)). The accuracy of the system was reported as less than 1% of the total travel distance, where the accumulated positioning error is calculated as the 2-D distance between the start and stop positions of the traversal path. An accuracy analysis of wireless sensor network-based indoor localization measurement, using weighted centroid localization method (WCL) and relative-span exponential weighted localization method (REWL), has been presented (Pivato, Palopoli, and Petri (2011)). The experimental results show that using 4 anchors with the contribution weight of each anchor being 1, the WCL method achieves the RMS of 1.29 metres. Furthermore, in the case of the REWL method, using 4 anchors with the weighting factor being 0.1, the achieved RMS is 1.27 metres.

Positioning results can also be reported in terms of their probability function. For example, an ultrawideband-based indoor positioning method has been developed, taking advantage of a map of measurement noise and particle filter to improve position estimation (Suski, Banerjee, and Hoover (2013)). In this work, there were 5.6 million positioning results obtained throughout the experimental areas. These results were used to build up probability functions of the positioning results, given the true positions. These probability functions were based on the assumption that the measurement noise is bivariate, mixture of Gaussian random variables. This resulted in ellipsoid boundary for positioning results.

In summary, various metrics have been used to report indoor positioning results. However, they only focus on articulating positioning errors, which are deviations from positioning results to the true position. While it is helpful, the sole use of positioning error in reporting the estimation of a positioning system is not enough, since it cannot convey other important estimation characteristics. For example, whilst positioning errors are different in different positions, they also tend to reside at certain directions with respect to the true positions. Furthermore, their dispersive level are also different regardless of positioning errors. This suggests that indoor positioning estimation is more than just the average or distribution of deviations between the estimated positions and the true position. Characterising positioning estimation is needed to provide a better understanding of positioning behaviour and performance of a system. In our work, we have identified a number of positioning estimation characteristics.

4. Positioning Estimation Characterisation

Characteristics of positioning estimation are not well-defined in the literature. In this work, we systematically analysed positioning data from 2 empirical studies, and observed that there are 3 key characteristics in positioning estimation: position accuracy, centroid consistency, and angular distribution. We define and propose new methods to metrics and measures for these characteristics.

4.1 *Position Accuracy*

Positioning errors, which are deviations from positioning results to the true position, are often used as means to report estimation performance. In our work, this characteristic is reflected through the position accuracy of the estimation.

Definition: Position accuracy is the measure of closeness, statistically of positioning results to the true position, where the closeness of a positioning result is calculated as Euclidean distance between that result and the true position.

$$\delta_T = \sqrt{(x - x_T)^2 + (y - y_T)^2} \tag{1}$$

where δ_T is the distance from a positioning result to the true position, which is also the *positioning error*; x and y are coordinates of the positioning result; x_T and y_T are coordinates of the true position.

Rationale: Positioning systems give estimation results to approximate the true position. Approximations may deviate from the true position. The bigger the deviations, the less reliable the estimation. Position accuracy reflects the reliability of the estimation in terms of deviations from estimation results to the true position.

Measure: In our work, the position accuracy is expressed in terms of the trueness and precision of the estimation (Adler et al. (2015)), which are measured by means of, respectively, the mean and variance of distances from positioning results to the true position. While the mean of distances indicates, on average, how close the positioning results are to the true position, the variance of distances indicates the spread of the distance values. The smaller the mean is, the closer, on average, the positioning results are to the true position, and hence the better. Moreover, the smaller the variance is, the more convergent the distance values are to the mean distance value, and hence the more precise the estimation is.

4.2 *Centroid Consistency*

The centroid is the average of all positioning results provided by the positioning system given each true position. While the position accuracy reflects how close the results are to the true position, centroid consistency refers to the way the positioning results are distributed. Note that the notion of centroid has been used in indoor positioning community (Blumenthal et al. (2007); Schmitt, Adler, and Kyas (2014)). For example, a weighted centroid localisation technique has been proposed, relying on the idea of calculating the position of devices by averaging the coordinates of known reference points. However, the notion of the centroid mentioned in these works is related to estimation techniques, or the centre of mass of geometric object(s). To our knowledge, the use of centroid in characterising the positioning estimation of a system has not been studied.

Definition: Centroid consistency is the measure of closeness among estimation results, in terms of geometric distribution, for a true position.

Rationale: The true position is unknown, but approximated by a positioning system. Approximation results may not coincide with each other. The more the approximations spread, the less consistent the estimation is. Centroid consistency indicates the stability of a positioning system in providing concurring approximations.

Measure: In our work, centroid consistency is analysed by examining how positioning results are distributed around their centroid. As such, we propose to measure centroid consistency in terms of the level of outliers and convergence. Note that the convergence is measured after outliers have been removed from the dataset.

- **Outliers**: An outlier is an observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism (Hawkins (1980)). In our work, outliers are positioning results that yield much farther distances to the centroid than others, where the centroid of the estimation is obtained by calculating the means of $x-$ and $y-$ coordinates of positioning results:

$$x_c = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2}$$

$$y_c = \frac{\sum_{i=1}^{n} y_i}{n} \tag{3}$$

  where x_c and y_c are x- and y-coordinates of the centroid; x_i and y_i, $i = 0...n$ are x- and y-coordinates of positioning results; n is the number of positioning results.

  An outlier is an extreme manifestation of the random variability inherent in the data, or the result of gross deviation from prescribed experimental procedure or an error in calculating or recording the numerical data (Grubbs (1969)). In our work, outliers are detected using boxplots, where a box represents distance data ranging from the first quartile (25th percentile) to the third quartile (75th percentile); the length of the box is also called *interquartile range*, and the two hinges of the box are identified using *Tukey's Hinges.* A solid line in the box indicates the value of the median. Outliers are then considered as values that fall outside 1.5 interquartile ranges from the upper or lower hinges. Extreme outliers are considered as values that fall outside 3 interquartile ranges from the upper and lower hinges.
- **Convergence**: Convergence is the measure of how concentrating around the centroid positioning results are. Positioning systems producing more diverging positioning results are less consistent, since repeating positioning estimation at the same position may yield results that deviate from each other.

  In our work, convergence is measured using the mean and the variance of distances from positioning results to their centroid. The mean of distances shows, on average, how close the positioning results are to the centroid. The smaller the mean is, the more concentrating positioning results are, and hence the better. Besides, the variance of distances indicates the spread of distance values around the mean; the smaller the variance is, the more convergent positioning results are.

4.3 *Angular Distribution*

Besides position accuracy and centroid consistency, the directions with respect to the true position, in which positioning results are concentrating, are also a characteristic of positioning estimation. In our work, this characteristic is defined as angular distribution.

Definition: Angular distribution is the measure of how positioning results are distributed in terms of their angles with respect to the true position.

Rationale: Positioning systems provide approximations of a true position. Angular distribution shows the bias of the approximation toward certain directions from the true position. The angular bias is reported using the mean angle and the spread. Knowing the angular bias will provide a measure to understand the approximation tendency at a position.

Measure: We apply directional statistics (Mardia and Jupp (2009)) to calculate the mean and variance of angles as angles are of circular nature, and consequently, for e.g., 0 degrees and 360 degrees are identical angles. The directional mean and variance of the angle values are calculated as follows:

$$\bar{\theta} = \begin{cases} \arctan(\sum_{i=1}^{n} \sin\theta_i,\ \sum_{i=1}^{n} \cos\theta_i) & \text{if } \sum_{i=1}^{n} \cos\theta_i \geq 0 \\ \arctan(\sum_{i=1}^{n} \sin\theta_i,\ \sum_{i=1}^{n} \cos\theta_i) + \pi & \text{if } \sum_{i=1}^{n} \cos\theta_i < 0 \end{cases} \tag{4}$$

$$directionalVar(\theta) = 1 - \frac{\sqrt{(\sum_{i=1}^{n} \cos\theta_i)^2 + (\sum_{i=1}^{n} \sin\theta_i)^2}}{n} \tag{5}$$

where $\bar{\theta}$ is the directional mean of angles to the true position; $directionalVar(\theta)$ is the directional variance of angles to the true position; θ_i, $i = 1...n$ are angles from positioning results to the true position; n is the number of positioning results; the inverse tangent function 'arctan' takes values in $[-\pi/2, \pi/2]$.

The mean angle indicates the direction where positioning results are concentrating. The variance of angles indicates the spread, ranging from 0 to 1; the higher the variance, the more dispersed the angles are. If the angular data are widely dispersing, then the variance will be almost 1. On the other hand, if the angular data are tightly clustered, then the variance will be almost 0. Since the angular data are circular and not normally distributed, we apply *Chebyshev* inequality on angular data to calculate the range of angles around the mean that covers at least certain percentage of positioning results (Mardia and Jupp (2009)):

$$Pr(|\sin(\frac{1}{2}(\theta - \bar{\theta}))| \geq \epsilon) \leq \frac{directionalVar(\theta)}{2\epsilon^2}, \quad 0 < \epsilon < 1 \tag{6}$$

where θ is the random variable denotes the angle, $\bar{\theta}$ is the directional mean angle, and $directionalVar(\theta)$ is the directional variance of angles.

5. Experiments

In this section we describe a set of empirical measurement experiments that we carried out to validate our positioning metrics. These were carried out in two different indoor locations using two different RFID carriers - a NAO robot and a human.

5.1 *Experimental Equipment*

We used an active RFID-based Real Time Location System (RTLS), available commercially[1], to estimate indoor position. The RTLS hardware in our experiment consists of one main reader, five auxiliary readers and a number of active RFID tags. Fig. 1 shows the architecture of the system. The system functions as follows: the RFID tags communicate with the readers (including the main reader) using RFID signal. Based on the signal received, the readers calculate the distance, *ranging information*, between them and the RFID tag. All information received and

[1] We are currently not able to disclose the manufacturer of the system due to confidential terms

calculated by the readers is forwarded to the main reader via a WiFi connection. The main reader uses triangulation to compute the position, *positioning result*, of the RFID tag.

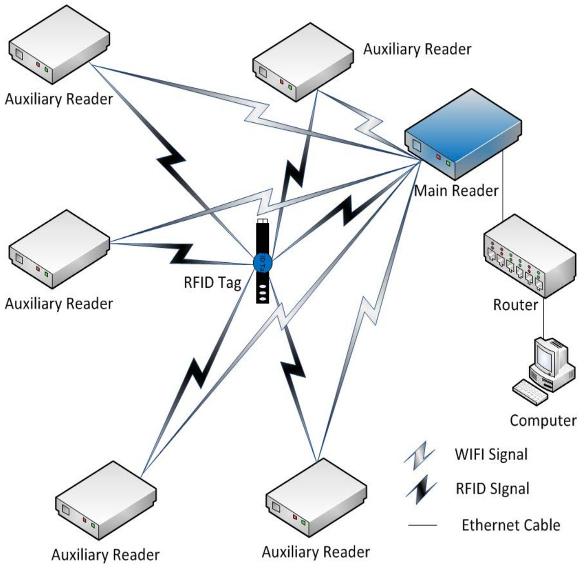

Figure 1. The architecture of the active RFID RTLS system used in the experiment.

We took a large number of positioning results of a RFID tag within a room and compare them to its known actual positions. To do so, we adopted a novel solution of using a NAO robot to carry the RFID tag and traverse through our experimental areas. The use of the robot was to assure the accuracy of its position, and the repeatability of a robot to travel a path many times with high degree of accuracy. As shown in Fig. 2, the RFID tag was put on top of a pole, carried by the NAO robot. In our experiment, we programmed the NAO robot to use a camera positioned on his chin to follow a pre-defined path. The robot also used its WiFi connection to communicate with the RTLS software in the computer. We describe the detailed experimental procedure in Section 5.2

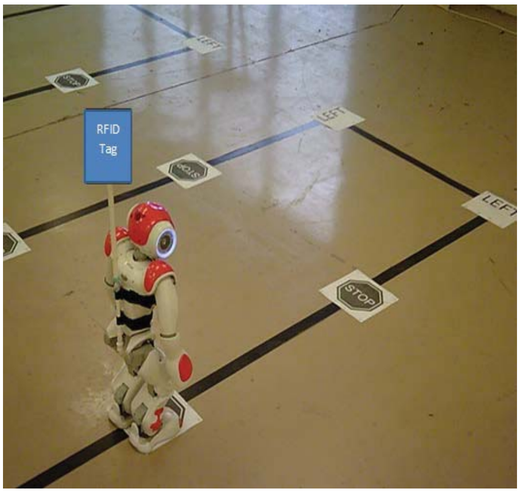

Figure 2. The NAO robot carrying the RFID tag on top of a pole and traversing through a pre-defined path.

In addition to using the NAO robot, the RFID tag was also carried on either the right or left hand of a person. The height of the tag when carried by the person was similar to when it was carried by the NAO robot. These additional experiments were carried out to test if a human body influences the positioning estimation. In these experiments, the person used a phone to communicate with the RTLS software, and to log timing information (described in Section 5.3) while traversing the area. We developed an application to run on an Android phone to accomplish this task. In our experiment, we used a Samsung Galaxy S phone for this purpose. Details about the logs and their use are presented below.

5.2 *Experimental Procedure*

We conducted our experiments at two locations. The first location was at the warehouse of an industry partner - Adilam Technologies. The second location was at an university laboratory room. The maps of the experimental areas and the traversal paths are shown in Fig. 3. The experimental areas in the laboratory and Adilam warehouse are, respectively, 5.4x6.15 m^2 and 7.08x16.2 m^2. We chose the laboratory location to represent a medium-sized, cluttered single indoor office environment. We chose the Adilam location to represent a larger, more open indoor environment with connected room.

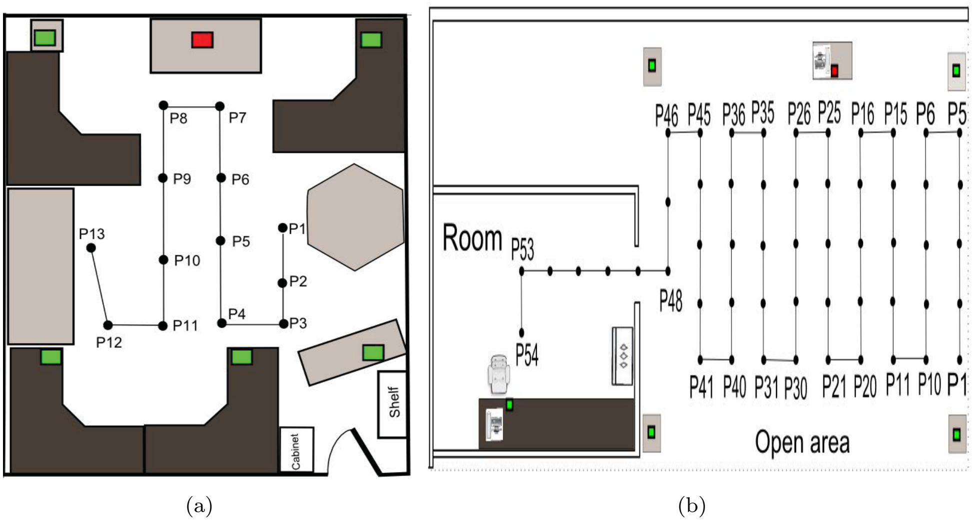

Figure 3. The map of experimental areas: (a) is the map of the laboratory; (b) is the map of Adilam warehouse. The blue boxes are the auxiliary readers; the red boxes are the main reader; the dark grey objects are desks; the light grey objects are tables; P1, P2, ..., P54 are the experimental points constituting the traversal path in each environment, there are 13 experimental points at the laboratory and 54 experimental points at Adilam warehouse.

There were three experimental settings applied for each environment. The first setting used the NAO robot to carry the RFID tag; the second and third settings used a person wearing the RFID tag on their, respectively, right and left hands. The robot and the person traversed a pre-defined path. The height of the RFID tag when carried by the robot was also the same as the height when it was carried by a human. Furthermore, the robot's movement was done by flexing its legs, hence imitating a human's movement.

In each experiment, the following procedure was followed:

- We created a path in each of the experimental areas by carefully measuring and then taping the floor. At pre-defined positions on the path, we used labels to guide both human and robot movement, i.e., *Stop* label, *Right* label and *Left* label.

- We manually measured the coordinates of each label. The results of this measurement were the true positions of the labels. These true positions were measured with respect to the main reader's position.
- We had a human wearing the RFID tag or the NAO robot carrying the RFID tag traverse along the path. The active RFID tag was a wearable wrist band. When worn by a human or carried by the robot, the tag was always positioned directly above the path. During the traversal, the human or the NAO robot needed to communicate with the RTLS software and log certain information. We developed an Android application, in the human case, and programmed the NAO Robot, in the robot case, to accomplish these tasks. The following mechanism was adopted during the path traversal:
  - All the readers were set up and configured using the RTLS software. Then, the RTLS software waited for a starting signal, sent by either the human or the NAO robot, before logging the positioning results and ranging information into a file.
  - To signal the start of the experiment, the human or the robot sent a signal to the RTLS software. Upon receiving the starting signal, the RTLS software logged the starting time, and continuously logged the positioning results and ranging information with their corresponding time stamp.
  - Upon arriving at a label, the arrival time was logged. Note that the arrival time at the first label was also the starting time of the phone or NAO logging. After this, the human or the robot stayed upon the label for 6 seconds. During this period, multiple positioning measures were made by the RTLS system. If the label was the *Stop* label, then after staying on the label, the human or the robot kept going straight. If the label was the *Right* or *Left* label, then the human and the robot performed, respectively, the right turn or left turn while staying on top of the label, and then went straight.
  - Upon leaving a label, the departure time was logged.
  - For each experimental setting, the traversal process was repeated 30 times so that the positioning results at each point can be statistically tested.

5.3 *Data Collection Mechanism*

After a human or the robot had traversed the path, we had two types of log file: one log file was created by the RTLS software, which stores the starting time, the positioning results and ranging information with their corresponding time stamp; the other was created by the phone application or the NAO robot, which stores the corresponding arrival and departure time at each label. Since we know the true location of each stop, given these 2 files, we can compare the accuracy of the measured positions using time as the correlation factor.

The comparison of the true position to the measured position depends on the synchronisation of the clocks of the RTLS system and logging of the true position. We synchronised time recorded by the respective clocks through the data logs. The accuracy of the time difference is in tenths of milliseconds.

5.4 *Experimental Results*

We illustrate our method with positioning results at positions 1 and 2 at the laboratory (see Fig. 3(a)) in the NAO robot case as examples [1]. Figs. 4 and 5 show the aggregated positioning results for, respectively, positions 1 and 2. The x and y axes are relative to the main reader (in metres), in 2 dimensional space. We proceed by analysing these results in terms of the position accuracy (Section 5.4.1), the centroid consistency (Section 5.4.2), and the angular distribution (Section 5.4.3).

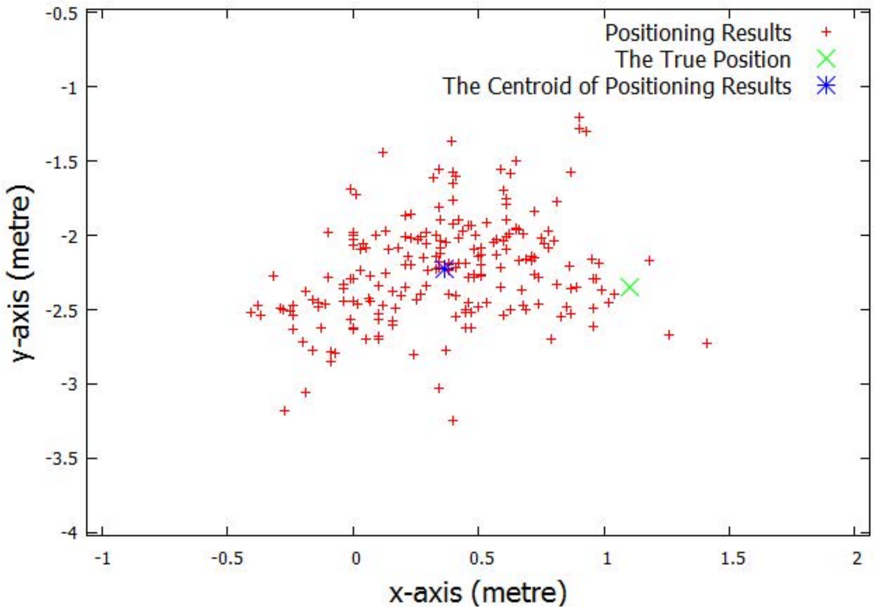

Figure 4. Positioning results at position 1 in the laboratory using the NAO robot.

5.4.1 *Position Accuracy*

Fig. 6 shows the histograms of distance values from, respectively, positioning results at positions 1 and 2 to their true position. It can be seen that, on average, the positioning results at position 1 are farther from their true position than those at position 2 from their true position. This is reflected in the mean distance of these positions, in which the mean distance at position 1 is 0.82 metres while the mean distance at position 2 is 0.69 metres. Furthermore, it is shown that the distances from positioning results at position 1 to their true position spread out more than those at position 2 to their true position. This means that the measurement errors at position 1 are less converging than those at position 2. This is indicated in the variances of distances, from positioning results of these two positions to their corresponding true positions. For position 1, the variance is 0.11 while for position 2, the variance is 0.09.

5.4.2 *Centroid Consistency*

Fig. 7 shows a box-plot of distances from positioning results at position 1 to their centroid. As shown in the figure, there are 5 results that are considered as outliers since the distances from these results to the centroid fall outside of the normal range, within which the majority of results reside. On the other hand, positioning estimation at position 2 yields no outlier.

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[1] The full results under each experimental setting can be found in *http://opax.swin.edu.au/∼ldlam/Appendix-PositioningCharacterisationResults.xlsx*

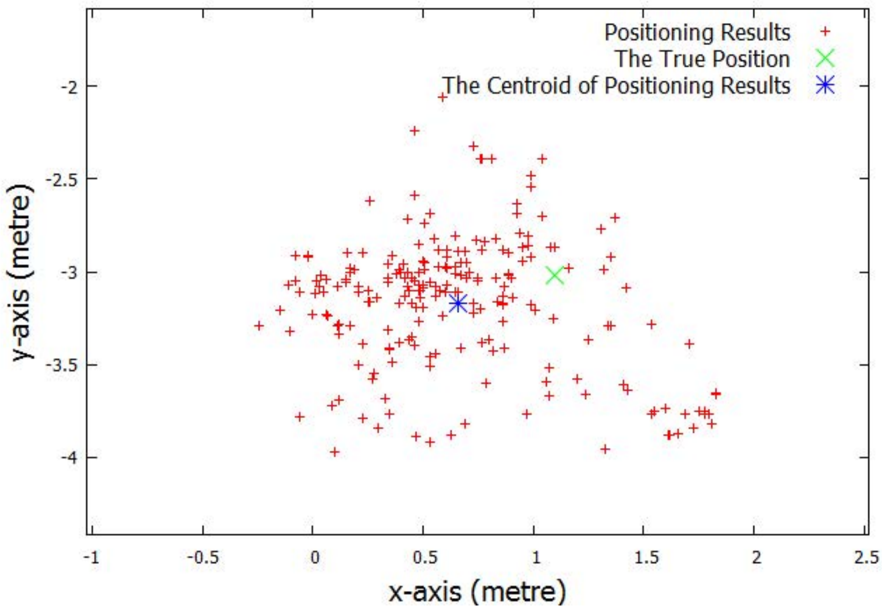

Figure 5. Positioning results at position 2 in the laboratory using the NAO robot.

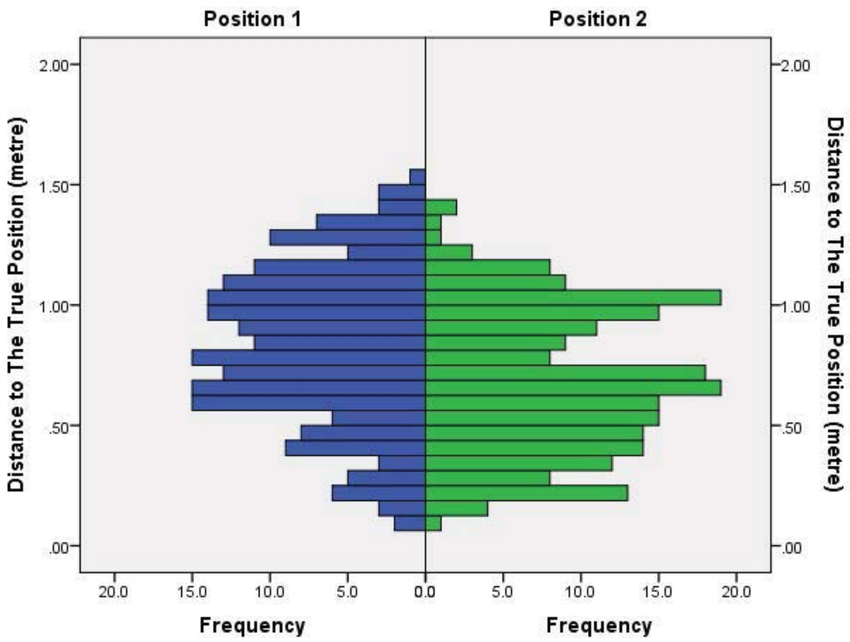

Figure 6. Histogram of positioning distances to the true position at positions 1 and 2 in the laboratory using the NAO robot.

Fig. 8 shows the histograms of distances, from positioning results at positions 1 and 2 to their centroid. It can be seen that positioning results at position 1 are closer to their centroid than those of position 2. This is indicated through the means of distances at positions 1 and 2. In position 1 case, the mean distance is 0.42 metres, smaller than that in position 2 case, being 0.5 metres. Furthermore, the variance of the estimation at position 1, being 0.05, is also smaller than that of the estimation at position 2, being 0.09.

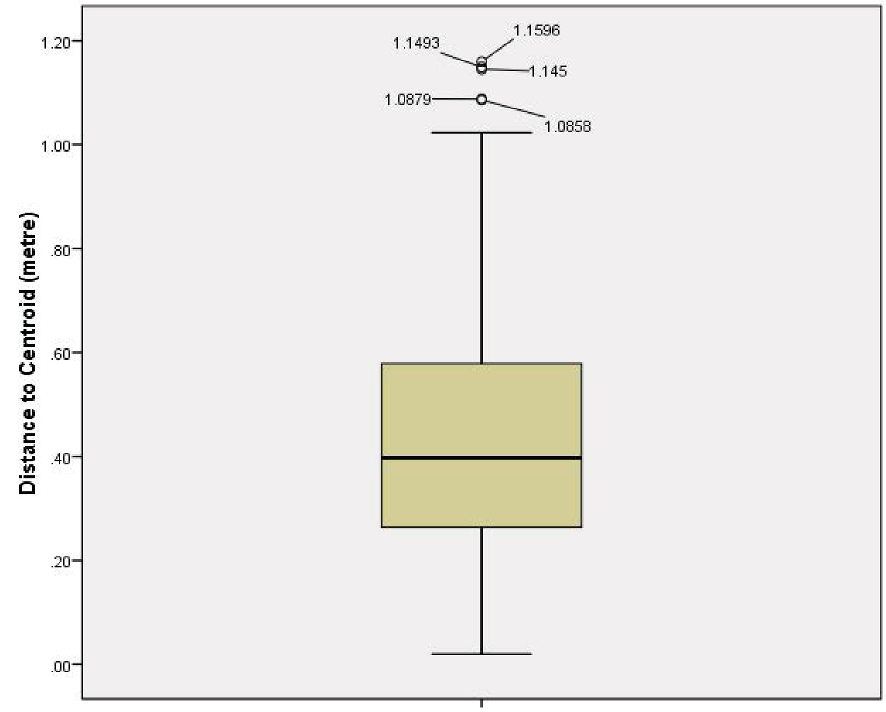

Figure 7. Box-Plot of distances from positioning results at position 1 to their centroid. The plot shows that there are 5 results that fall outside of 1.5 interquartile ranges; hence, they are considered as outliers.

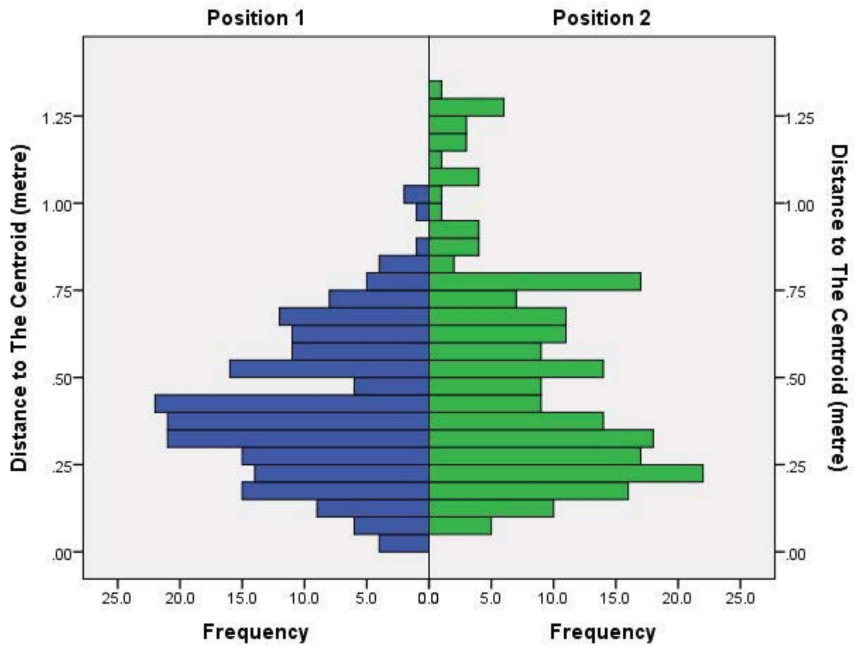

Figure 8. Histogram of positioning distances to the centroid at positions 1 and 2 in the laboratory using the NAO robot.

5.4.3 Angular Distribution

The positioning results of positions 1 and 2, as depicted in Figs. 4 and 5, show that the positioning estimation at position 1 tends to distribute toward certain directions from the true position, while that at position 2 tends to disperse more around the true position. This is in line with the histograms of angular data at positions 1 and 2 in Fig. 9. The figure shows that, in the position 1 case, the angles concentrate at the direction from 150 to 200 degrees, while, in the position 2 case, the angular distribution reaches its peak at around 200 degrees. The figure also shows that the angular distribution in the position 2 case also spreads out to other values more than that in the position 1 case. In fact, the angular mean values of positions 1 and 2 are, respectively, 170 degrees and 193 degrees. This indicates that the positioning estimation of positions 1 and 2 is concentrated at around these orientations. Furthermore, the angular variance values of positions 1 and 2 are, respectively, 0.1 and 0.36. This indicates that the spreading level in the position 1 case is less than that in the position 2 case.

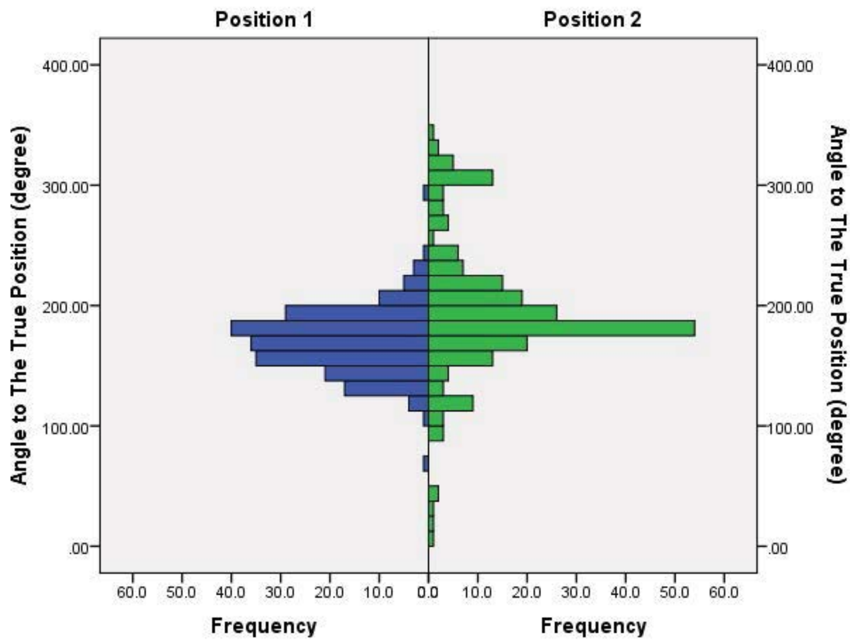

Figure 9. Histogram of positioning angles to the true position at positions 1 and 2 in the laboratory using the NAO robot.

Consider the 50% case. Applying Equation 6 on the angle data shows that the angular range that covers at least 50% positioning results at position 1 is from 132.45 degrees to 207.81 degrees, while that at position 2 is from 119.53 degrees to 266.17 degrees. The results are depicted in Fig. 10, in which the *distribution areas*, formed by the 2 angular boundary lines and an arc, are where the majority of positioning results reside in. The arc is part of the circle, whose centre is the true position and the radius is determined by the farthest point in the angular range from the true position.

6. Interpreting and Using Positioning Characteristics

We have identified and analysed 3 characteristics of indoor positioning estimation. We have illustrated methods that we used to measure these characteristics, using positioning results at positions 1 and 2 in the laboratory and the NAO robot case as examples. In this section, we discuss the meaning of the characterisation results in assessing the performance of a positioning estimation process (Section 6.1), and the use the characterisation in different cases (Section 6.2).

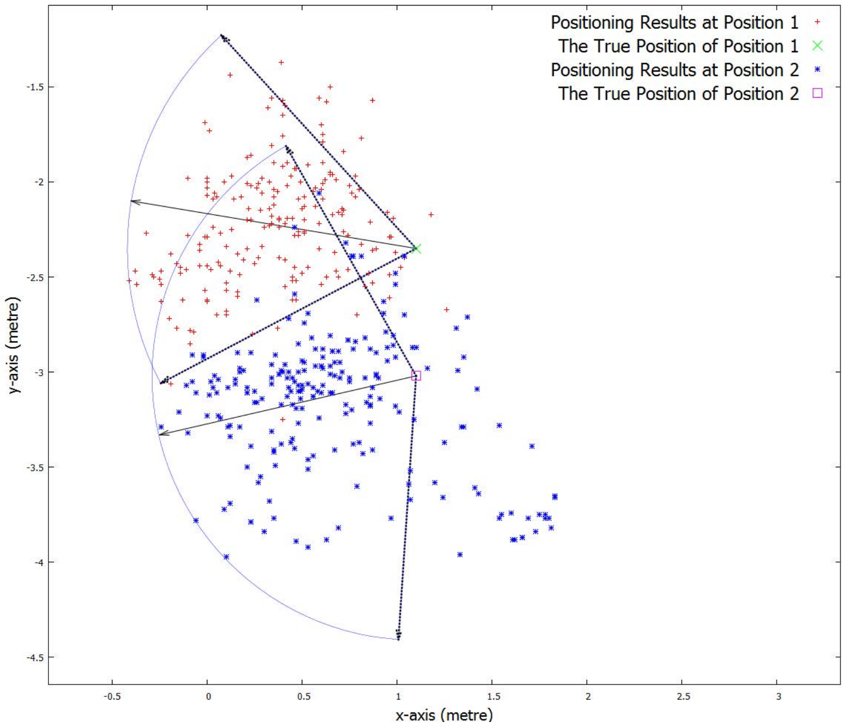

Figure 10. The angular and distance ranges that cover at least 50% positioning results at positions 1 and 2 using *Chebyshev inequality*. The solid arrows originate from the true positions and denote the mean angles. The broken arrows denote the boundaries of angular ranges. The blue arcs show the boundaries of the distance ranging from the true position.

6.1 *Assessing the performance of an estimation process*

Current indoor positioning research utilises positioning error, which is the Euclidean distance from positioning result to the true position, as a means to measure the performance of an estimation process. While positioning error is a useful measure of positioning performance, there are other characteristics, such as the convergence of positioning results or the bias in the estimation process, that have not been studied. Our characterisation results can capture all these characteristics, and hence can be used to provide a more holistic assessment of an estimation process.

Position accuracy refers to the closeness of positioning results to the true position. In our work, the measurement of position accuracy is based on the notion of positioning error, which has long been used in the literature. The meaning of position accuracy in characterising the performance of an estimation process is interpreted based on the trueness and precision of the measurements, which are measured by, respectively, the mean and variance of positioning errors. Specifically, the smaller the mean and variance are the better, as it indicates a more accurate and precise estimation of the tracked target's position. For example, the mean and variance of positioning errors at position 1, respectively 0.82 metres and 0.11, are larger than those at position 2, respectively 0.69 metres and 0.09. As such, in terms of accuracy, the estimation at position 2 is better than the that at position 1.

Centroid consistency measures the number of outliers in the estimation process, and the convergence of positioning results. The more outliers in the results, the less stable the estimation is. Furthermore, the more convergent the positioning are, the more consistent the estimation is. As such, estimation with less outliers and more convergent results is more preferred. For example, the estimation at position 1 produces 5 outliers while that at position 2 yields no outlier; hence, the estimation at position 2 is more stable. Besides, the mean and variance of distances - from positioning results to their centroid - at position 1, respectively 0.42 metres and 0.04, are smaller than those at position 2, respectively, 0.5 metres and 0.09. This indicates that the estimation process at position 1 yields more convergent results than that at position 2.

Angular distribution measures the distribution of positioning results in terms of their angles with respect to the true position. The angular distribution can show the angular bias of an estimation process. For example, as depicted in Fig. 9, the estimation process at position 1 is biased toward the 170-degree direction while that at position 2 is biased toward the 193-degree direction. Furthermore, the spreading level at level 1 is less than that position 2. This is reflected in the angular variances at these 2 positions, which are 0.1 at position 1 and 0.36 at position 2. This suggests that the estimation at position 1 is more biased than that at position 2.

Fig. 11 shows the percentiles representing the frequency of positioning results and their distances from the true position. It can be seen that distances at position 1 are consistently farther away from the true position than those at position 2. For $25th$, $50th$, $75th$, $100th$ percentiles, the values at positions 1 are, respectively, 0.62 metres, 0.85 metres, 1.09 metres, and 1.52 metres; while those at position 2 are, respectively, 0.46 metres, 0.67 metres, 0.95 metres, and 1.39 metres. This is also consistent with the position accuracy at these 2 positions, where positioning estimation at position 1 is less truthful than that at position 2.

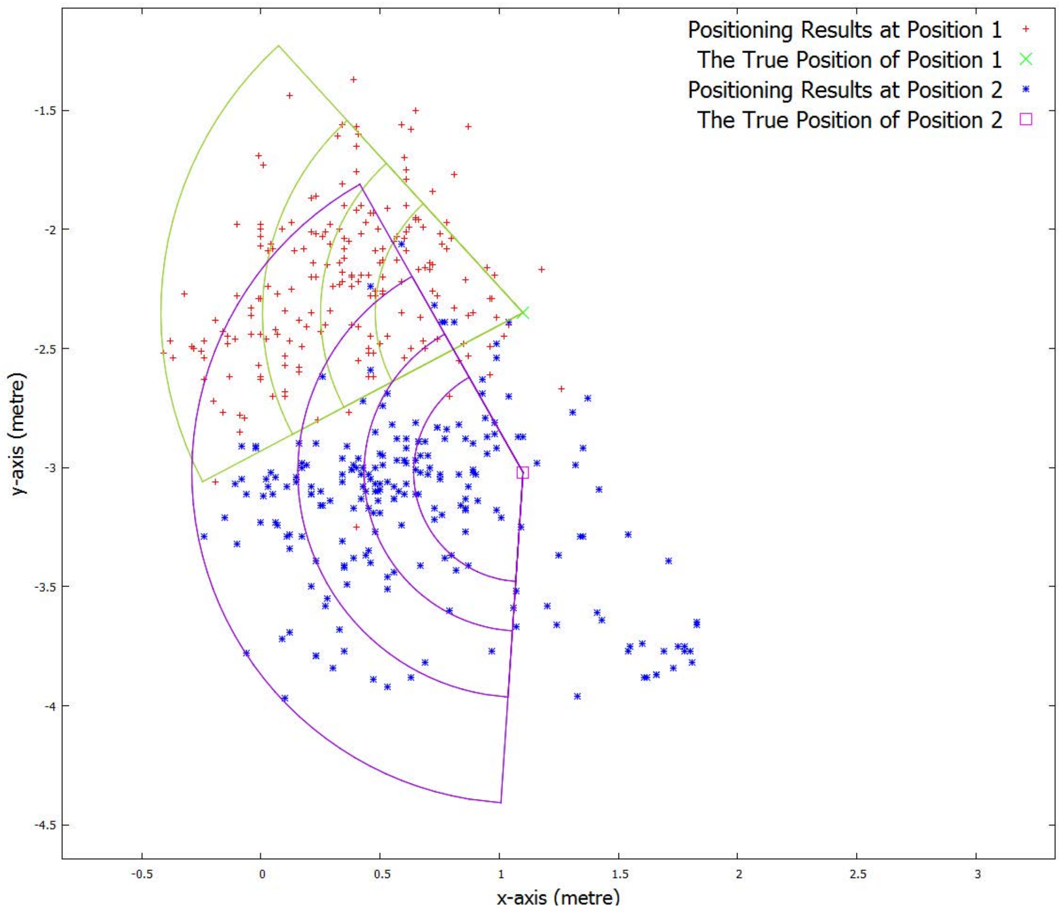

Figure 11. Percentiles of distances from positioning results inside the distribution areas to the true position at positions 1 and 2. The 4 arcs at each position, from innermost to outermost, are, respectively, $25th$, $50th$, $75th$, $100th$ percentiles.

Besides, Fig. 12 shows the percentiles representing the frequency of positioning results and their distances from the centroid. It can be seen that the values at $25th$ and $50th$ percentiles at these 2 positions are quite similar, with those at position 1 being, respectively, 0.26 metres and 0.39 metres while those at position 2 being, respectively, 0.26 metres and 0.44 metres. However, at $75th$ and $100th$ percentiles, the values at position 2 (respectively, 0.7 metres and 1.32 metres) are larger than those at position 1 (respectively, 0.56 metres and 1.02 metres). This further consolidates that the estimation at position 1 is more convergent than that at position 2.

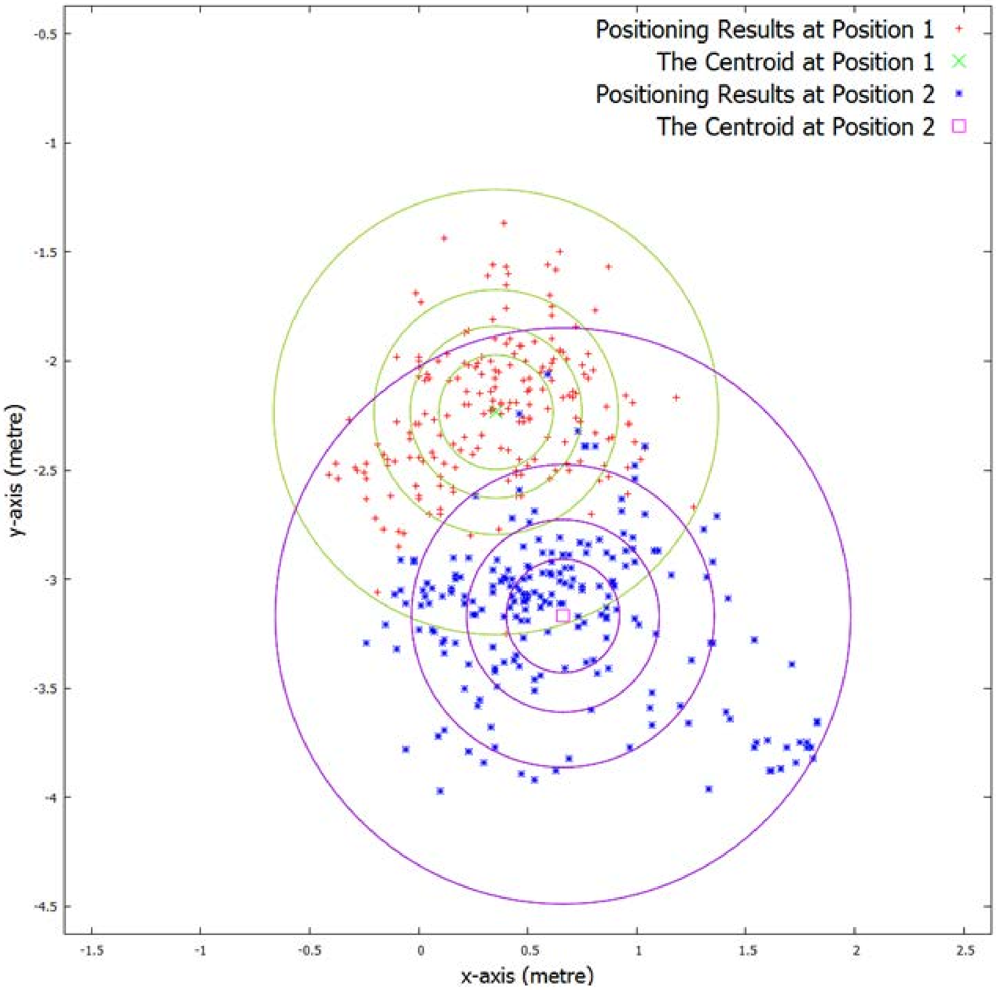

Figure 12. Percentiles of distances from positioning results to the centroid at positions 1 and 2. The 4 circles at each centroid, from innermost to outermost, are, respectively, $25th$, $50th$, $75th$, $100th$ percentiles.

6.2 *Using the characteristics*

Our positioning characterisation can be used in 2 ways: comparing the estimation at different positions in an area, and comparing the estimation across different settings such as using the NAO robot as traveller and using human as traveller.

6.2.1 Comparing the estimation at different positions in an area

After characterising the positioning estimation at all positions in our experiment, we pick 3 positions to compare their characteristics. This comparison provides an example to illustrate how the characteristics can be interpreted. The comparison is shown in Table 1. We first compared the estimation at positions 3 and 1. It can be seen that the position accuracy at position 3 (i.e. $(0.53, 0.05)$) is smaller than that at position 1 (i.e. $(0.82, 0.11)$), which means that estimation at position 3 is more accurate than that at position 1. Position 3 has angular distribution that is more evenly spaced out, which is reflected in its directional variance (i.e. 0.24) compared with that at position 1 (i.e. 0.1). The centroid consistency at position 3 (i.e. $(0.33, 0.03, 1.08\%)$) is smaller than that at position 1 (i.e. $(0.42, 0.04, 2.4\%)$), which suggests that the estimation at position 3 is more convergent and contains fewer outliers than that at position 1. Overall, the estimation at position 3 is better than that at position 1 across all 3 characteristics.

Table 1 also shows the comparison between the estimation at positions 1 and 10. The table shows that the estimation at position 1 is less accurate than that at position 10, which is reflected in the position accuracy at these 2 positions (i.e. respectively $(0.82, 0.11)$ and $(0.67, 0.1)$). Furthermore, the directional variance at position 1 (i.e. 0.1) is smaller than that at position 10 (i.e. 0.62), which suggests that the estimation at position 1 is more biased than that at position 10. However, the centroid consistency at position 1 (i.e. $(0.42, 0.04, 2.4\%)$) is smaller than that at position 10 (i.e. $(0.6, 0.11, 5.4\%)$), which means that the estimation at position 1 is more convergent and contains fewer outliers than that at position 10. Overall, the estimation at position 1 is worse than that at position 10 in terms of position accuracy, angular distribution, but is better in terms of centroid consistency.

Table 1. Comparing the estimation at 3 positions in the laboratory in the NAO robot case. P1, P3, and P10 indicate, repectively, positions 1, 3, and 10. The tuple in the **Position Accuracy** row shows, respectively, the mean and variance of distances from positioning results to the true position. The tuple in the **Angular Distribution** row shows the directional variance of angles from positioning results to the true position. The tuple in the **Centroid Consistency** row shows, respectively, the mean and the variance of distances from positioning results to the centroid and the percentage of outlier in the estimation. The comparison shows which result is better than the other.

Positions	**Comparison**	
Positions 3 and 1	Position Accuracy	P3(0.53, 0.05) > P1(0.82, 0.11)
	Angular Distribution	P3(0.24) > P1(0.1)
	Centroid Consistency	P3(0.33, 0.03, 1.08%) > P1(0.42, 0.04, 2.4%)
Positions 1 and 10	Position Accuracy	P1(0.82, 0.11) < P10(0.67, 0.1)
	Angular Distribution	P1(0.1) < P10(0.62)
	Centroid Consistency	P1(0.42, 0.04, 2.4%) > P10(0.6, 0.11, 5.4%)

6.2.2 Comparing the estimation across different experimental settings

The positioning characteristics can be used for comparing an estimation under different experimental settings over the same trajectories, such as the estimation in the NAO robot case and the estimation in the cases the human wearing the RFID tag on the left ("the left hand case") and right hands ("the right hand case"). Table 2 shows the comparison between estimation under different settings in our experiment. The results were calculated using aggregated positioning results obtained in each setting.

At the laboratory, it can be seen that the NAO robot case provides the most accuracy and least biased estimation results compared with the left hand and right hand cases, which is reflected in the position accuracy and angular distribution characteristics. For example, the position accuracy in the NAO robot case (i.e. $(0.65, 0.12)$) is smaller than those in the left hand and right hand cases (i.e. respectively $(0.75, 0.17)$ and $(0.79, 0.16)$); furthermore, the directional variance in the NAO robot case (i.e. 0.85) is also larger than those in the left hand and right hand case (i.e. respectively 0.62 and 0.6), which suggests that the angular distribution in the NAO robot case is more evenly spaced out than those in the left hand and right hand cases. In terms of centroid consistency, the percentage of outlier in the NAO robot case (i.e. 2.86%) is the smallest compared with those in the left hand and right hand cases (i.e. respectively 3.53% and 4.26%), which means the estimation in the NAO robot case is more stable than those in the left hand and right hand cases. However, the estimation in the right hand case provides the most convergent results than those in the NAO robot and left hand cases, which is evident through the mean and variance of distances to the centroid in the right hand case (i.e. $(0.45, 0.07)$) compared with those in the NAO robot case (i.e. $(0.47, 0.07)$) and left hand case (i.e. $(0.5, 0.08)$).

At the warehouse, the table shows that the position accuracy in the left hand case (i.e. $(0.9, 0.24)$) is smaller than those in the NAO robot case (i.e. $(0.92, 0.29)$) and the right hand case (i.e. $(0.95, 0.31)$), which suggests that the estimation in the left hand case is more accurate than those in the NAO robot and right hand cases. The angular distribution in the left hand case is also more evenly spaced out compared with those in the NAO robot and right hand cases, which is evident through the directional variance in the left hand case (i.e. 0.9) compared with those in the NAO robot and right hand cases (i.e. respectively 0.82 and 0.55). In terms of centroid consistency, the estimation in the left hand case (whose mean and variance values are $(0.48, 0.09)$) produces more convergent results than those in the right hand and NAO robot cases (whose mean and variance values are, respectively, $(0.5, 0.09)$ and $(0.76, 0.2)$); however, the estimation in the NAO robot case is the best in terms of percentage of outlier (i.e. 3.99%) compared with those in the left hand case (i.e. 5.21%) and right hand case (i.e. 5.35%).

Table 2. Comparing the estimation across different experimental settings. Each tuple in the **Mean** and **Variance** rows of **Position Accuracy** shows the value of, respectively, the mean and variance of distances from positioning results to the true position. Each tuple in the **Directional Variance** row of **Angular Distribution** shows the directional variance of angles from positioning results to the true position. Each tuple in the **Mean**, **Variance**, and **Percentage of Outlier** rows of **Centroid Consistency** show, respectively, the mean and variance of distances from positioning results to the centroid, and the percentage of outlier in the estimation. The NAO, LEFT, and RIGHT indicate, respectively, the NAO robot case, the left hand case, and the right hand case. The comparison shows which result is better than others.

Location	**Characteristics**	**Comparison**	
Laboratory	**Position Accuracy**	Mean	NAO(0.65) > LEFT(0.75) > RIGHT(0.79)
		Variance	NAO(0.12) ≥ RIGHT(0.16) > LEFT(0.17)
	Angular Distribution	Directional Variance	NAO(0.85) ≥ LEFT(0.62) > RIGHT(0.6)
	Centroid Consistency	Mean	RIGHT(0.45) > NAO(0.47) > LEFT(0.5)
		Variance	RIGHT(0.07) ≥ NAO(0.07) > LEFT(0.08)
		Percentage of Oulier	NAO(2.86%) > LEFT(3.53%) > RIGHT(4.26%)
Warehouse	**Position Accuracy**	Mean	LEFT(0.9) > NAO(0.92) > RIGHT(0.95)
		Variance	LEFT(0.24) > NAO(0.29) > RIGHT(0.31)
	Angular Distribution	Directional Variance	LEFT(0.9) > NAO(0.82) > RIGHT(0.55)
	Centroid Consistency	Mean	LEFT(0.48) > RIGHT(0.5) > NAO(0.76)
		Variance	LEFT(0.09) ≥ RIGHT(0.09) > NAO(0.2)
		Percentage of Oulier	NAO(3.99%) > LEFT(5.21%) > RIGHT(5.35%)

In this section, we have shown that the three positioning characteristics can be used to represent accuracies of each position as measured by a RTLS system, it can also be used to characterise and compare RTLS systems for a whole trajectory. Comparing with other approaches in the literature, our characterisation method can be used to compare not only the position accuracy of the estimations, but also whether the estimations are biased, convergent and stable. For example, a survey of experimental evaluation in indoor localisation research has been conducted (Adler et al. (2015)), where various metrics used to evaluate positioning performance are analysed including: *trueness*, *precision*, *accuracy*, *distribution*, and *sample size*. Apart from *sample size*, other metrics are related to the notion of measurement error, which is the deviation from positioning result to the true position. As such these metrics can only reflect how close positioning results are to the true position, they cannot articulate if the estimation is biased, convergent and stable. A number of metrics to assess the performance of different wireless indoor positioning techniques and systems have been proposed (Liu et al. (2007)). Among the proposed metrics, those related to positioning outcomes are *accuracy* and *precision*. In this work, *accuracy* is defined as location error which is usually reported in terms of mean distance error to the true position, while *precision* is reported in terms of distribution of distance error between the estimated positions and the true position. As such, these 2 metrics correspond to the position accuracy characteristic in our work; however, other characteristics of the estimation (i.e. angular distribution and centroid consistency) are not studied. A survey of indoor positioning systems for wireless personal networks has been conducted (Gu, Lo, and Niemegeers (2009)). In this work, *accuracy* and *precision* have been used to assess the performance of positioning systems in terms of positioning outcome. The *accuracy* is defined as the average error distance, and the precision means the success probability of position estimations with respect to pre-defined accuracy. As such, these metrics are the measured of closeness from positioning results to the true position. Our characterisation method - including 3 characteristics: position accuracy, angular distribution, and centroid consistency - can be used to assess not only the closeness of positioning results to the true position, but also whether the estimation is biased, convergent, and stable.

7. Threats to Validity

In our work, we conducted a set of empirical measurement experiments in order to measure and study the positioning estimation of an active RFID-based RTLS. In this section, we discuss key threats to validity of our findings.

Threats to Construct Validity: We set out to measure and characterise positioning estimation at two different indoor locations that were available to us. There are confounding factors, such as furniture, surrounding object's material, etc., in the environments that may significantly influence the positioning results. However, our main goal was to better understand positioning estimation and develop a method to characterise it. While the positioning results can be affected, they do not have any impact on the characterising method.

Threats to Internal Validity: We conducted our experiments using the RFID-based RTLS, the NAO robot and a mobile phone. As the time in the log files are only precise to tenths of milliseconds, there is a time synchronisation difference between the measured position and the true position. In order to ensure the accuracy in extracting positioning results, we stopped at each position for 6 seconds. This adequately compensates for such time difference between the log files.

Threats to External Validity: We used a particular brand and technology in our experiments. Therefore, the positioning results obtained may be specific to the system used. Whilst the measured results cannot be generalised because of that, the characterisation method is general.

8. Conclusion

Indoor positioning estimation is typically characterised in terms of deviations from positioning results to the true position. Important characteristics such as angular bias and positioning convergence have not been studied. The key contributions of this paper are the introduction of centroid consistency and angular distribution in characterising accuracy, and a method for systematically characterising an indoor positioning estimation using all 3 characteristics: position accuracy, centroid consistency, and angular distribution. As an example application domain of these techniques, we used an active RFID-based real time location system in order to demonstrate our new characterisation methods. The positioning results were obtained through empirical measurement experiments, conducted under various conditions, and using both the NAO robot and human.

Our proposed new characteristics give a quantitative analysis of the estimation performance of a positioning system. Specifically, position accuracy indicates how truthful the positioning are, and is measured in terms of the mean and variance of positioning errors. The smaller the mean and the variance are, the better. Centroid consistency is a measure of how consistent positioning results are. In our work, the centroid consistency of an estimation process is measured in terms of the number of outliers in the results, and the convergence of the results with respect to their centroid. Estimation with less outliers and more convergent results is more preferred. Lastly, angular distribution articulates the angular bias of an estimation. While the mean angle shows the biased directions, the variance of angles indicates the level of bias. The smaller the variance, the less biased the estimation.

These characteristics also reflect the positioning tendency of a system in terms of where positioning results tend to be distributed given a true position. As such, the knowledge of these characteristics will be useful in developing statistical models to improve raw positioning results. This is a focus of our future work, which would also include conducting further experiments in different environments with different technologies.

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Table 3. List of figure captions.

Figure number	Caption
1	The architecture of the active RFID RTLS system used in the experiment
2	The NAO robot carrying the RFID tag on top of a pole and traversing through a pre-defined path
3	The map of experimental areas: (a) is the map of the laboratory; (b) is the map of Adilam warehouse. The blue boxes are the auxiliary readers; the red boxes are the main reader; the dark grey objects are desks; the light grey objects are tables; P1, P2, ..., P54 are the experimental points constituting the traversal path in each environment, there are 13 experimental points at the laboratory and 54 experimental points at Adilam warehouse
4	Positioning results at position 1 in the laboratory using the NAO robot
5	Positioning results at position 2 in the laboratory using the NAO robot
6	Histogram of positioning distances to the true position at positions 1 and 2 in the laboratory using the NAO robot
7	Box-Plot of distances from positioning results at position 1 to their centroid. The plot shows that there are 5 results that fall outside of 1.5 interquartile ranges; hence, they are considered as outliers
8	Histogram of positioning distances to the centroid at positions 1 and 2 in the laboratory using the NAO robot
9	Histogram of positioning angles to the true position at positions 1 and 2 in the laboratory using the NAO robot
10	The angular and distance ranges that cover at least 50% positioning results at positions 1 and 2 using *Chebyshev inequality*. The arrows originate from the true positions and denote the mean angles. The green lines denote the boundaries of angular ranges. The blue arcs show the boundaries of the distance ranging from the true position
11	Percentiles of distances from positioning results inside the distribution areas to the true position at positions 1 and 2. The 4 arcs at each position, from innermost to outermost, are, respectively, $25th$, $50th$, $75th$, $100th$ percentiles
12	Percentiles of distances from positioning results inside the distribution areas to the centroid at positions 1 and 2. The 4 circles at each centroid, from innermost to outermost, are, respectively, $25th$, $50th$, $75th$, $100th$ percentiles