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Passive RFID Rotation Dimension Reduction via Aggregation

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By:

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Abstract

Radio Frequency IDentification (RFID) has applications in object identification, position, and orientation tracking. RFID technology can be applied in hospitals for patient and equipment tracking, stores and warehouses for product tracking, robots for self-localisation, tracking hazardous materials, or locating any other desired object. Efficient and accurate algorithms that perform localisation are required to extract meaningful data beyond simple identification. A Received Signal Strength Indicator (RSSI) is the strength of a received radio frequency signal used to localise passive and active RFID tags. Many factors affect RSSI such as reflections, tag rotation in 3D space, and obstacles blocking line-of-sight. LANDMARC is a statistical method for estimating tag location based on a target tag's similarity to surrounding reference tags. LANDMARC does not take into account the rotation of the target tag. By either aggregating multiple reference tag positions at various rotations, or by determining a rotation value for a newly read tag, we can perform an expected value calculation based on a comparison to the k-most similar training samples via an algorithm called K-Nearest Neighbours (KNN) more accurately. By choosing the average as the aggregation function, we improve the relative accuracy of single-rotation LANDMARC localisation by 10%, and any-rotation localisation by 20%.

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Contents

Acronyms

2D Two Dimensional.

3D Three Dimensional.

ANN Artificial Neural Network.

AoA Angle of Arrival.

ASK Amplitude Shift Keying.

CPU Central Processing Unit.

EPC Electronic Product Code.

GPS Global Positioning System.

ID Identification.

KNN K-Nearest Neighbours.

LANDMARC LocAtioN iDentification based on dynaMic Active Rfid Calibration.

LMMSE Linear Minimum Mean Square Error.

ML Machine Learning.

MMSE Minimum Mean Square Error.

MSE Mean Square Error.

OOK On-Off Shift Keying.

PL Path Loss.

RBF Radial Basis Function.

RBFNN Radial Basis Function Neural Network.

RDA Rotation Dimension Abstraction.

RDR Rotation Dimension Reduction.

RF Radio Frequency.

RFID Radio Frequency IDentification.

RSSI Received Signal Strength Indicator.

UHF Ultra High Frequency.

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Chapter 1

Thesis Layout

The Problem

Radio Frequency IDentification (RFID) localisation has many challenges described in Section 3.4. It is the goal of localisation algorithms, most of which are described in Section 3.3, to overcome these challenges to improve the accuracy of estimated tag locations. RFID tag Received Signal Strength Indicator (RSSI) values fluctuate based on the path of the signal from and back to the antenna. Rotating an RFID tag changes the pathloss described in Section 2.4. We expand on this rotation fluctuation problem and how it affects localisation in Section 4.2.

Importance

It is important to solve localisation problems to improve the accuracy of localisation algorithms. By improving the accuracy of said algorithms, applications such as those discussed in Section 3.2 can more accurately fulfill their purpose, thereby improving the performance of their application.

Previous Solutions

We discuss previous solutions in Section 4.4 where additional sensors, as well as moving antennas, have solved the rotation challenge. These algorithms and applications utilize additional sensors or additional system complexity to solve the problem, whereas we aim to utilize only pre-existing information of an RFID localisation system with stationary antennas.

New Solution

Our solution to improving machine learning algorithms on inconsistent sinusoidal data involves reducing the dimension of the sinusoidal training data via an aggregation function. This reduction allows a more accurate comparison between a newly read sample at a specific instance of the sinusoid function. An example would be sampling the tide at a single unknown time t while the tide follows a periodic function of t. This process is described in Section 5.2.

Thesis Statement

For any dataset that contains a periodic dimension for which newly gathered instances exist at only one unknown value within the period, we can improve the accuracy of distance comparisons between such newly read instances and training data by reducing the dimension of the training data via an aggregation function.

Originality

State of the art localisation algorithms seldom discuss the orientation of the passive RFID tags that they wish to localise. Our solution uniquely considers solely the pre-existing information in an RFID localisation system to solve the challenge that tag rotations introduce to machine learning localisation.

Non-Triviality

It is logical to hypothesize that single-orientation localisation with both training and target tags at solely the same orientation serves as a lower bound on localisation distance error, since the rotation challenge has been removed from the system. We have found that this is not the case. We first aggregate the RSSI of incorrect rotations into our training data. We then use the aggregated data to perform localisation with an increased accuracy relative to systems with no rotation solution. This process is shown in Section 5.2.

Proof

We demonstrate our thesis empirically by performing a localisation algorithm called LANDMARC on a variety of rotational data. The results of our experiment are shown in Section 6.3. We explain our performance increase by testing the accuracy of the K-Nearest Neighbours algorithm used by LANDMARC. Our results for the K-Nearest Neighbours comparison are shown in 5.4.

Explanation

We explain in 5.4 that our improvement in accuracy is because each RSSI at a single rotation has inherent noise due to the walls and objects in an enclosed environment. Since any one rotation may be unreliable, we aggregate the information of multiple different rotations to reduce the noise that exists at a singular rotation. This results in more accurate comparison, and therefore improved accuracy.

Other Discplinary Uses

This thesis applies to applications that use training data of a sinusoidal nature. It allows for more accurate comparison of newly read samples that can only exist at a single value within that sine wave, where noise may exist. Examples of such data are tidal shifts, and yearly seasonal changes such as in temperature.

Conclusion

By using Rotation Dimension Reduction on LANDMARC training data, we have aggregated the training data in the rotation dimension to allow for more accurate comparison of newly read samples. This has improved our LANDMARC localisation accuracy by 20% in the general case, and by 10% in a perfect rotation prediction system. Future work includes analyzing such factors as the material of the object to which a tag is attached, the effect of different aggregation functions, and the possibility of including other rotation axes. We expand further on future work in Chapter 7.

Chapter 2

Radio Frequency Identification

Radio Frequency IDentification (RFID) is the product of radar - discovered in 1935 - used during World War II to detect war planes at a far distance. Although no identification capabilities existed to distinguish friendly from foe planes, according to [22] German pilots would roll their planes, which would change the reflected radio signal. This allowed the crews on the ground to perform vague identification. This is thought to be the first application of RFID. Various research was conducted throughout the 1950s and 1960s with published works on how radio waves could be used to identify objects. Commercial applications, such as stores, still use transponder technology that indicates whether or not an item has been paid for. Patents started to be issued for applications in transponders in the 1970s, when the United States government started to develop RFID systems.

An RFID system can obtain the strength of a signal detected by a transceiver. Physics equations can be used to estimate a distance between a transceiver and a signal, but with modern computers we can also utilize algorithms that can compute an estimated position for the source of a signal. Estimating the position of a signal source is important because of the source of signal is physically attached to an object and follows the object's movements, then this position estimate for the signal's source is also an estimate for the object on which the signal source is attached. This allows the tracking of an object, useful for a variety of applications.

2.1 Object Identification via Unique Code

RFID systems allow the identification of any object onto which an RFID tag is placed. RFID tags are small metal tags that consist of a peice of memory than can be written to and read from using radio frequency waves. These waves can operate at a variety of frequencies, most of which are designated for general purpose short-range communication. By modulating a unique code into the signal, a receiving antenna can demodulate the signal to determine which tag was read. The tags, along with one or more antennas form a general purpose object identification and tracking system for use in various applications.

Barcodes are an example of another object identification technology. Even though barcodes are prominently used in industry, RFID offers industry more features than barcodes at a slightly higher cost. Barcode technology utilizes lasers, and therefore requires a reader to have line-of-sight vision of its target as described by [13], and according to [25] has a short range at which a reader can identify the barcode - up to a few feet. Conversely, even though line-of-sight is useful for RFID, radio waves can pass through certain objects, and reflect around them, meaning that line-of-sight is no longer important. As well, radio waves have a greatly increased range over the resolution of most laser optic readers used in barcodes. However, RFID tags are more expensive than barcodes, but are reusable. Barcodes can be printed for as cheap as the ink costs to print them, and therefore disposed of cheaply. RFID tags require specific cuts of metal, making it more expensive, and therefore important to retain every tag. Therefore, in applications such as grocery stores, where packaging is often disposed of, RFID tags could prove to be too expensive to be practical.

2.2 Active and Passive Tags

Passive RFID, patented in the United States in 1975 under Patent US4023167, and later extended in 1986 under Patent US4688026, is a technology described to identify metallic tags using a radio frequency antenna. According to the patents, if the antenna is sufficiently close to the tag, meaning the Radio Frequency (RF) Signals can hit the tag through materials and reflections, the tag will excite with energy from the radio frequency burst. It then modulates this signal, thereby changing the amplitudes of the electric wave, using an on-board circuit and emits this signal from the tag. The antenna is then able to read this modulated signal and extract the information contained inside of the electric signal's amplitudes via demodulation to determine the unique EPC of the tag. An antenna can also determine how much energy the received signal contains — the electrical gain it receives — from the identified tag's signal, which results in a useful received signal strength indicator value.

Active RFID, patented in 1993 under US5448110 as ”Enclosed Transceivers”, utilizes a concept similar to passive RFID. The difference is that active RFID has a self-contained battery that powers the circuitry. This means that rather than reflecting a signal, and thereby doubling the required travel distance of a signal, active RFID only requires one transfer of energy. Since active RFID does not need an original signal to power the tag, antennas can function on a listen-only mode. Usually, an active tag will send bursts of signal followed by a period of no signal to save battery lifetime. While passive tags theoretically last as long as they stay intact, active RFID tags only send signal as long as their battery's lifetime.

Passive RFID tags are cheaper to make than active ones due to their simple components. The disadvantage of passive RFID tags are that their antennas must be equipped to both send and receive RFID signals, and are therefore more extensive than the antennas required by Active RFID. Since passive tags are cheaper to make, multiple tags can be placed throughout an environment as references for use in localisation, but the expensive antennas must be placed carefully to reduce the overall cost of the system. Active RFID tags are more expensive, but have cheaper listen-only antennas. Due to their advantages and disadvantages, some algorithms may be viable for one type of tag that become expensive with the other; passive tags are less expensive to use in algorithms that require a large amount of static reference tags in the environment.

2.3 RFID Antennas and Polarization

RFID systems work on the principal of creating electric fields with which two devices can communicate. It is important to understand the physics of an RFID antenna to properly orient them within the identification environment. This is to maximize the signal strength received by the tag to improve the quality of the signal, useful for demodulating the information within the signal, as well as for localising the tag.

RFID systems consist of a pair of antennas that can communicate between each other using radio frequency signals. Antennas can more easily read signals that have the same polarity as themselves. Polarization is used to signify the behaviour of the electric field vector, as shown in 2.1. If the polarization of a signal does not match an antenna, the ability of the receiving antenna to gain electrical charge from the signal could be reduced, resulting in lower RSSI values, similarly a possible loss of information. Antennas can be linearly polarized, or can be made to polarize circularly. Each type of polarization has benefits for different applications.

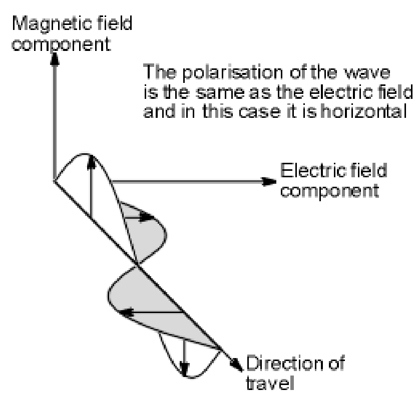

Figure 2.1: Linear polarization depicted by [32].

Linear polarization causes electric waves to oscillate in a particular plane. To receive these signals efficiently, a receiving antenna must be polarized in the same direction. Figure 2.2 depicts an ineffective rotation for linearly polarized antennas, whereas if Circular polarization is used, the tag can be read similarly in both orientations as shown in Figure

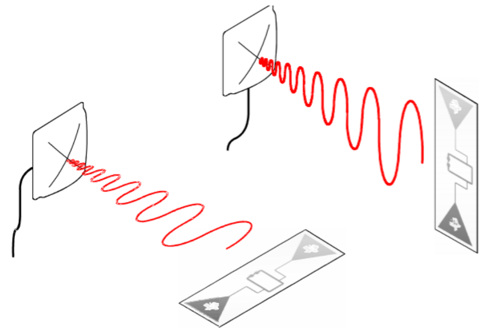

Figure 2.2: Orientation with reduced gain efficiency for linear polarization [21].

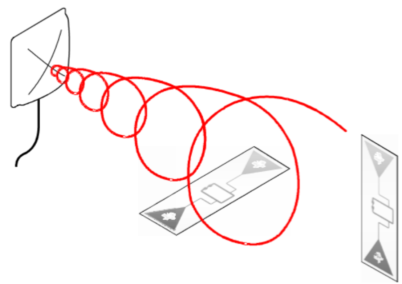

Figure 2.3: Circular polarization on the same tag orientations as Figure 2.2 [21].

2.3. Circular polarization can be imagined as a linearly polarized antenna rotating on the axis of propagation. If imagined, the tip of the electric field vector will form a helix or corkscrew that propagates away from the antenna, and is the best way to visualize circular polarization according to [32]. The mutual polarization efficiency represents the ratio of energy received by one antenna given the polarization of another [28]:

$$p = \frac{1 + e_1^2 e_2^2 + 2e_1 e_2 cos(\theta_1 - \theta_2)}{(1+e_1^2)(1+e_2^2)} \tag{2.1}$$

where $e_1 e^{j\theta_1}$ and $e_2 e^{j\theta_2}$ represent the complex polarization ratios of the reader and tag antenna. The absolute value of e of the above equation is related to the axial ratio A as [24]:

$$A[dB] = 20log\left|\frac{e+1}{e-1}\right| \tag{2.2}$$

An example is given by [14] where if a circularily polarized reader antenna has an axial ratio of 0 dB, and the tag antenna is linearly polarized, the equations give us that the best possible polarization efficiency is 0.5, thereby translating to 70% of the maximum possible tag range.

2.4 Antenna Gain and Path Loss

Antenna gain can be calculated in free space using Equation 2.3 given by [5]. It can be seen that the power received by the antenna is directly related to the power and gain efficiency of the antenna (P_t and G_t), wavelength frequency λ, distance from the antenna r, as well as the gain efficiency of the passive tag G_{tag}.

In our case, we have a wavelength frequency that changes between 50 distinct frequencies in the 902 to 928 MHz frequency band. We account for these varying frequencies by averaging the RSSI taken at all frequencies into a single RSSI value. We also use a constant power value, and constant antenna gain efficiency. With these factors taken into account, the only variable in this equation becomes the distance. Since this equation is given in free space, we also must deal with sources of reflection, line-of-sight obstruction, and interferences. We aim to solve this using our proposed method.

RSSI is the electrical gain of an antenna receiving a signal. We can calculate RSSI in dB as the ratio of the amount of energy outputted relative to the amount of energy received. This is expressed by [5] as:

$$G_{dB} = 10log\left(\frac{P_{out}}{P_{in}}\right) = 20log\left(\frac{V_{out}}{V_{in}}\right) \tag{2.3}$$

where P describes power outputted and inputted as joules, and V describes voltage outputted and inputted as watts. This gives us an idea of what the value of RSSI means relative to the amount of power transfered. Even though this is the way to calculate RSSI given the output and input power values, we cannot directly calculate the distance due to possible path loss.

Radio signal propagation between two communicating antennas is an important factor in determining signal strengths, and therefore RSSI. Within most practical environments, there will be several sources of reflection from transmitter to receiver antennas. An equation for solving path-loss information given each source of reflection is given by [18]:

$$L_{path} = \left(\frac{\lambda}{4\pi d}\right)^2 \left|1 + \sum_{n=1}^{N} \gamma_n \frac{d}{d_n} e^{-jk(d_n - d)}\right|^2 \tag{2.4}$$

where λ is the frequency of the signal in hertz, d is the distance travelled by the direct ray from source to destination without reflection in meters, γ_n is the reflection coefficient of the n^{th} relfected ray due to the type of material that reflected it, d_n is the total distance of the n^{th} reflected ray, k is Coulomb's constant, and N represents the total nuber of reflections in the propagation environment. Path loss can be proportional to d^{-n} depending on the environment, where the the path loss exponent n can vary from 1 to 6.

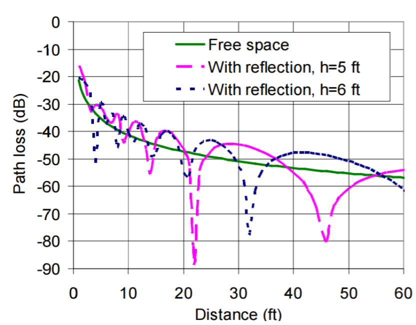

Figure 2.4: A graph of distance vs path loss with and without reflections by [14].

The log-distance path loss model introduced in [27] aims to model how a signal's power changes due to distance away from an antenna. This empirical model is constructed in various environments, due to possible reflections and dampening materials. By using the empirical parameters determined in [27], relative distance between a transmitter and receiver can be estimated despite the existence of reflected signal, and obstruction of line-of-sight via:

$$\bar{PL}(d)[dB] = PL(d_0)[dB] + 10 \times n \times log_{10}\left(\frac{d}{d_0}\right) \tag{2.5}$$

$$PL(d)[dB] = \bar{PL}(d)[dB] + X_\sigma[dB] \tag{2.6}$$

where $\bar{PL}(d)[dB]$ is the mean path loss of the signal in dB, n is the mean path loss exponent from 1 to 6 for one's particular environment, $PL(d)[dB]$ is the path loss of the signal in dB, $PL(d_0)[dB]$ is taken to be the the path loss of a reference free-space propagation from source to target at 1 meters away, therefore d_0 is taken as the direct propagation reference distance (1m) in meters, d is the direct distance between transmitter and receiver in meters, and $X_\sigma[dB]$ is a random variable with standard deviation σ in dB. The parameters n and σ were determined using minimum mean square error (MMSE) linear regression on sample readings in a variety of environments. A table of the parameter values can be found in [27]. Figure 2.4 shows a distance versus path loss graph with reflections and no reflections. We can see that reflections fluctuate path loss.

2.5 Passive RFID Backscatter

Passive RFID tags are metal tags that receive a signal, and reflect that signal with modulation, as first discussed by the early work [29]. This reflection process is called backscattering. The antenna that sends the signal also receives this modulated signal, and can identify the tag by demodulating the signal. On/Off Shift-Keying (OOK) or Amplitude

Shift Keying (ASK) can be used to represent digital data within a sinusoidal wave, as compared in [26]. Active tags do not use backscattering, they instead send a modulated signal using their own batteries. In addition to the tag's ID, other information can be modulated within the signal, including data from memory banks contained within the tag itself. Tags have small read-write memory banks located on the tag that can be powered by RF waves and returned to the communicating antenna as described in [19]. These memory banks can be used for storing additional small pieces of information onto the tag itself.

The concept of backscatter allows a reader to receive reflected, modulated radio frequency waves from a passive RFID tag. The energy with which this signal returns is known as the Received Signal Strength Indicator (RSSI). This value is given in dBm - the loss of power below a one Milliwatt reference returned by a signal. For example, a signal returning with 0.1 mW of power results in a loss of 10dBm. Signal strengths usually fall into the range of [-90,-30] dBm where -30 dBm is a clear signal, and -90 dBm is a faintly recognized, failing signal. The importance of determining RSSI is that, among many factors, the distance with which a signal must propagate to reach an antenna is related to a loss in signal strength.

Chapter 3

RFID Localisation

3.1 Object Tracking and Localisation

Although radio technology was used for identification purposes, and shortly after that was utilized in mass communication, recent advances in antennas have allowed the gathering of vital information such as phase shift and RSSI for use in localisation algorithms - algorithms for finding an estimated position of an RFID tag in up to 3 dimensional space. A common equation used in passive RFID localisation is the Path Loss Prediction Model. The path loss model discussed by [27] relates RSSI to distance by detecting how weak the signal strength becomes at various distances. This empirical formula has been used in many passive RFID localisation approaches to simulate algorithms in virtual environments. It is also used to estimate the distance for use in geometric estimations of position, such as the trilateration technique used in GPS. Before efficient algorithms existed, physics equations helped to estimate distances to and from receivers based on physical properties of radio waves. Distance estimations using trilateration, similar to GPS, are insufficient because of the RSSI error margins of backscattered signals within certain environments.

Localisation can be performed using a variety of sensors: infrared distance or ultrasonic distance sensors can be reflected off objects in the environment to detect change in relative distance of an object, thereby tracking its location; cameras can be used with image processing to track objects, identifying them by their shape, as well as detecting their relative positions based on the angle, position of the camera, as well as pixel size of the object; signals can be reflected off of a transceiver which both identifies the object to which the transceiver is attached, as well as an estimated position based on the RSSI of the transceiver. Each type of localisation has benefits and disadvantages.

Sensors that detect relative distance of objects do not provide automatic object differentiation, and therefore require algorithms or prior knowledge of the objects being tracked. Also, an array of such sensors must be used to detect movement in any spatial axis. Camera sensors allow easier distinction of objects than distance sensors, but still require algorithms to differentiate objects and calculate relative position. Localisation systems that utilize signal processing of transceivers gain automatic object detection, as long as tranceivers are pre-defined as to which object they belong to. However, an object may be physically separated from its designated transceiver, and may not accurately represent the true position of the desired object. This is an unacceptable disadvantage in applications where a tranceiver is likely to be tampered with, such as in security, and a camera may be more suitable.

3.2 Applications

Wu [13] discusses many applications in which RFID is used. Logistics is a popular application of RFID for companies in the manufacturing and managing of goods. RFID allows recognizing the location of a particular item in the supply chain, and when it had arrived or departed. Retail can utilize RFID to determine which items are being bought, or even stolen, by customers [25]. Healthcare can use the identification and localisation capabilities of RFID to track admitted patients, as well as important medical equipment [20]. Security systems - even venue entrances for events - can utilize RFID to provide or deny access to certain RFID tags, owned by specific individuals. Robotics utilizes RFID technologies to improve the self-localisation of robots by identifying and localising itself with respect to its environment. Advances in RFID technology could improve each of these applications, and provide efficient and effective means of tracking and identification.

In patient care homes and hospitals it is very important to keep track of patients for both the safety of the staff as well as the patient. Using RFID technology along with localisation algorthms, it is possible to track every staff member and patient by assigning unique RFID tags to them and attaching them to the user. If done in a secure way, staff members are able to see the location of all staff, which is useful for security reasons. Staff can also monitor the locations of each patient. Since monitoring patients takes human resources, if the task is made easier and more localised, then less human resources are needed. Therefore, less staff members may be required by introducing RFID localisation to a hospital environment.

RFID localisation can also be used by industrial warehouses that seek to increase the efficiency with which they find objects in their warehouse. Moving products faster can result in increased productivity, and therefore an increase in profits. This is performed by applying reusable RFID tags to each product in a warehouse, and subsequently performing localisation to find a product via the unique identification code given to an RFID tag.

3.3 Localisation Algorithm Categories

Algorithms for localisation can be categorized by the system's properties, as well as its estimation methods. We discuss each of these categories in detail, as well as compare each of their benefits.

3.3.1 Localisation by Moving Antennas

These methods of locating passive RFID tags utilize moving antennas to gain more information from the system. Since Antennas are the most expensive part of localisation systems, the less antennas one can use in a system, the less costly the system will be. Moving methods of localisation can cover ranges wider than solely an antenna's signal strength by moving the antenna around the desired area. This will however result in less constant coverage of any single area over time.

Rotational approaches such as [16] place an RF antenna on a rotating apparatus that allows the scanning of 360 degrees with the antennas as the center. This author's particular method scans angular sectors around the center in a range of power levels. With the utilization of bayesian networks, antennas can use angular information, as well as the minimum power level required to read the tag for localising the tag. The benefit of this approach is that a wide area can be covered with each antenna, and the maximum error of distance should be low. The disadvantage of this method is the time required to scan each angular sector at each power level, as well as the added cost to the system of rotating platforms. These platforms have moving parts, and could break down, hindering the system. This method also falls under Geometric Estimation.

Another type of antenna movement is the lateral movement along an axis. One such paper that uses this approach is [1]. The authors' method can cover a wide range using very few antennas. This method can get accurate readings of the position of an RFID tag at the cost of time spent moving the antennas across the room. The algorithm works by calculating the midpoint between when a tag starts being seen, and stops being seen during a period of movement. A visible minimal distance will usually exist if environmental factors are ideal. Ideal would mean no interfering objects residing in the straight path from the antenna to tag. If this is done along two axes, then a 2-dimensional position can be determined. Although these moving antennas can cover a wide 2 dimensional space using only 2 antennas, a problem may occur when the desired scanning area is larger than the distance an antennas signals can propagate.

3.3.2 Localisation by Machine Learning (ML)

Some methods of localisation rely more on statistical calculations like in machine learning. Different types of machine learning can be used, such as K-Nearest Neighbours, Kalman filtering, Bayesian networks, and neural networks. These algorithms require a training set of data to function, which can take time and effort to collect for whichever environment one is scanning. However, some of these methods allow the tracking of tags in a dynamic environment, ones with moving objects and reflections.

K-Nearest Neighbours Algorithm - LANDMARC

LANDMARC (LocAtioN iDentification based on dynaMic Active Rfid Calibration), an algorithm discussed in [23] and later extended to 3 dimensions in [12], is a type of machine learning that uses a grid-based training approach. In this method, a square grid of any unit size is composed using a reference tag at every unit step. The reference tags of this grid form the training set, where RSSI measurements can be collected before-hand, or while one is scanning for a new tag. RSSI data from a newly placed tag is compared to each tag of this training set. The K-most similar tags are chosen as the K-closest, and a weighted average is taken to determine the estimated X and Y coordinates of the new tag. A great advantage of using static reference tags to form the grid is that the system is tolerant of a dynamic environment as the reference close to one's new tag, and the new tag itself will be affected similarly by environmental shifts. Disadvantages to the system are finding the best parameter K for K-Nearest Neighbours, as well as greater inaccuracies near the border of the system due to the nature of choosing K-Nearest Neighbours. The authors of this method do not discuss the effect of tag rotations, as rotating a tag has an effect on RSSI measurements.

RSSI Kalman Filtering

This algorithm introduced in [15] utilizes a similar reference tag approach as LANDMARC, but estimates distances differently. Their algorithm estimates the distance to reference tags using the well-known log-distance path loss model for signal propagation. Since reference tags' locations are known, a distance error can be measured. Kalman filtering can minimize the error of distance estimations for each tag. This filter is applied to reduce the amount of noise in RSSI data collected from a tag. The authors summarize the method as finding the most likely position after intersecting two circles while applying kalman filtering to reduce noisy RSSI values. They make the assumption that the frequency is set at 915MHz, but this noise may be the result of readers using frequency hopping to switch between channels. This method requires training reference tags, which is an added complexity to the system. This method is also an example of Geometric Estimation.

Estimation using Artificial Neural Networks

Wagner [6] describes their application of Artificial Neural Networks (ANN) with RSSI as the input layer and a 2D coordinate as the output layer. They demonstrate their system using a variety of activation functions and learning functions while comparing mean squared error (MSE) of each. A downfall of this approach is the amount of time required to train the system to a specific environment. If the environment changes, a neural network trained on the past environment may perform poorly. The authors conclude that MSEs of 0.2 meters and below are possible. They state that this system has only been surpassed by a Radial Basis Function Neural Network (RBF).

Estimation using Radial Basis Function Neural Networks (RBF)

RBFNNs are neural networks that utilize a radial function to determine neuron activation values. Since this method uses techniques described in ANN, it has similar benefits, and suffers from similar drawbacks. RBFNN has been shown to be more accurate than ANN for tag localisation. Several approaches have been taken to improve the accuracy of RBFNNs such as the L-GEM method described in [8]. Another approach is described by [2] where fuzzy clustering is used to determine the center of the radial basis function used in the neural network. Guo [2] compares this new approach to L-GEM and LANDMARC, and claims improvement in accuracy. Overall, this approach appears to be a more accurate artificial neural network.

3.3.3 Localisation by Geometric Estimation

Geometric estimation methods attempt to estimate a tag's geometric positioning using the data read by an RFID reader. Many algorithms must utilize geometric estimation in some form to solve the localisation problem. Geometric estimation can however be used by itself. Calculating the intersection of shapes or vectors, or utilizing physics calculations among multiple antennas can be considered geometrical methods. Such a physics equation for use in geometrical estimation is the log-distance path loss model for estimating distance via signal strengths. These calculated distances allow us to estimate the tag's position geometrically.

Almost all antennas and readers have parameters changeable by the user. Algorithms that adjust parameters to gain more information, such as [16] that continuously alters the power levels at which the antennas run. This allows a distance calculation based on how the received signal changes between outputted power levels. This data is usually used for either a rotation estimation, or radius estimation from the antenna. Using multiple antennas, these values can be used to estimate a tag's position relative to the antennas using trilateration.

Shangguan [1] proposes a method of determining the Angle of Arrival (AoA) of a signal by using two antennas. In their approach, the first antenna sends out a signal and causes the passive tag to backscatter this signal. Then, another antenna picks up this signal and detects a phase shift. Since the location of the antenna is known, this change in phase can be used to calculate the angle between each antenna and the tag, which will intersect to the position of the tag.

3.4 Localisation Challenges

We compare the types of localisation that were discussed above to determine which approaches are best under which circumstances. For each sub-problem within RFID passive tag localisation, we will give the algorithm and system design that best solves that sub-problem.

3.4.1 Challenge 1: Environmental Changes

The purpose of a lot of RFID research is to determine how best to solve the problem of environmental changes. Changes in an environment are difficult to solve because there is not one equation or static parameter that can account for a change in its constants. For example, an RSSI reading from an antenna to a tag unimpeded would have a larger (less negative) decibel value than if an object were placed in the path between tag and antenna. Furthermore, the type of material that the object is made of can determine how significant this change is. Similarly, phase readings also change due to differing reflective surfaces. Some approaches to localisation have specific designs to solve this, while others do it naturally.

An approach that disambiguates environmental factors through the nature of its design is the localisation of RFID tags by moving antennas. The reason that this approach is not affected by environmental factors is because the RSSI value has little to do with calculating positioning, but rather the approach uses time and self-positioning to estimate geometry. Since objects decrease only RSSI values, the tag's position at the timings remains certain.

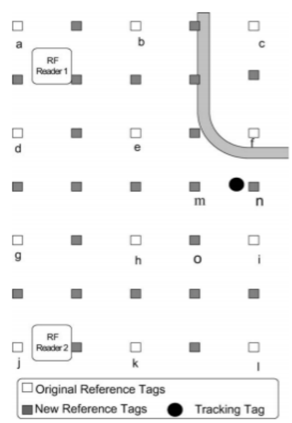

Figure 3.1: Visualization of LANDMARC by [Ni 2004]

Another approach that succeeds despite environmental changes is the LANDMARC system. This system requires reference tags be placed throughout the environment into a grid structure as shown in Figure 3.1. Since both the tag being tracked, as well as the reference tags that guide the position estimation are both affected by the same environmental factors, [23] claims that this approach provides similar results despite a dynamic environment. This is the only approach in Machine Learning applied to this problem that can inherently solve this problem as other machine learning methods utilize training inside of a static environment, or distance calculations via RSSI.

Geometrical estimation algorithms rely heavily on the values of data being read. For approaches that use physics equations such as the log-distance path loss formula based on RSSI, changes in values due to reflections as well as a changing environment can give incorrect calculations for distance. This approach requires other modules that can mitigate the effect of the environment and reflections, and therefore are not suitable on their own.

The only comparable approach for this problem are these two approaches. We see that one localisation system requires moving antennas, while the other requires cheap metal reference tags. Even though creating moving antennas is costly to the system, the LANDMARC approach is costly in terms of time required to train the system. Since time must be spent moving antennas while scanning anyway in the first approach, it can be argued that the LANDMARC system solves this subproblem more cost effectively. It is therefore noted as the best approach for solving this subproblem.

3.4.2 Challenge 2: Reflections

RFID passive tag systems are based on the concept of backscatter, as discussed earlier. This concept both allows us to use this technology, but can also hinder it. Backscatter works on other materials similar to RFID passive tags; signals can be reflected from walls, and other surfaces. These reflections can add a lot of noise to RSSI readings, as well as cause phase shift. We will determine the localisation approach that works best despite these reflections.

Some problems can occur with moving antennas and reflections. Take the example of an antenna rotating, the relative angle of an RFID tag is usually determined by RSSI readings as well as the midpoint between the first spotting and last spotting of the tag. In an empty space this may work very well, but a problem occurs when reflections from surfaces beside or behind the antenna still allow the antenna to detect the tag. In this case, approach that uses antennas moving along an axis, such as on a wall of a building, may perform better. Even though this approach may have less reflections due to probably being attached to a wall, a reflection could allow a tag to be seen earlier than usual, or later than usual during movement.

Algorithms that depend on changing parameters of the antennas do not work well for the problem of reflections due to the same issues as using solely physics equations or geometric estimations. All three rely on RSSI or phase values that may be too noisy due to reflections in the environment.

An approach that theoretically performs well despite reflections is machine learning. Each ML algorithm requires training to perform estimations. If the environment does not change, then reflections will also stay constant. Since the training data and newly seen instances will have the same sources of reflection, ML approaches will be able to estimate positions of tags similar to the case where there are no reflections. This is why machine learning approaches inherently solve the reflection problem.

Due to the ease with which machine learning algorithms can solve the problem of reflections in an environment, they are better than other methods in this respect. Since LANDMARC can also work with dynamic environments, it is the ML algorithm that is most useful for the reflection subproblem. Even though this is true, LANDMARC still boasts less average accuracy than ANN, which is 1 meter on average radially, and 0.2 meters (MSE) respectively.

3.4.3 Challenge 3: Tag Rotations

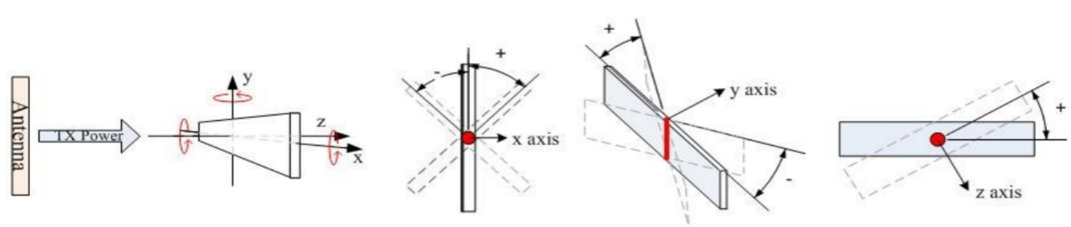

Figure 3.2: Depicting an example of the types of tag rotation [7].

Another subproblem of RFID passive tag localisation is locating a tag that has been rotated on any of its axes, as shown in Figure 3.2. Whichever directions the normal and negative normal are facing are the directions that will receive the strongest signal. If a tag is turned perpendicular to the singal source antenna, the antenna may not detect the tag at all, depending on reflections. As a tag rotates, depending on the objects in its proximity, the sources of reflections will change; the effect of reflections are discussed above. Even though tag rotations can drastically change RSSI values, and therefore localisation results, not many papers discuss this fact. Therefore, this could be an area of further improvement to the field of RFID passive tag localisation.

Since the approaches that require moving antennas do not rely heavily on actual RSSI values but rather change in value, rotations will not affect these methods drastically. There is, however, a moment in these systems where the relative angle of a tag to an antenna could be 90 degrees as the antenna moves. This means that at some rotation, there may be missing data that the system should ignore, or can be used as an indication of the tag's rotation. The authors of both moving antenna approaches do not discuss tag rotations in detail.

Machine learning approaches, depending on the type, could learn through the effects of rotations if given enough training data. Though not discussed in any of the papers presented in the machine learning section, rotations can have a large influence in RSSI and can sway predictions toward the direction of a tag's normal face. Since LANDMARC was performed using a single tag rotation, comparing a differing tag rotation to the training data could have poor accuracy. Neural networks are different, and require various training instances to learn an approximation function. In this case, using each rotation as an instance of the same position may allow the network to learn the effect of rotations. Each machine learning method may require a unique way of solving the rotation problem, but the best proposed approach would be to use each rotation as another training instance, and to allow the machine learning algorithm to learn the somewhat hidden effect of rotations.

Methods that are theoretically not as successful as machine learning, or moving antennas, are geometric estimations based on changing hardware parameters, or physics calculations. Since rotations of passive tags have the simulated effect of a world translation because of change in RSSI value, geometric estimations will theoretically predict the tag to exist at this simulated translation rather than its actual position. An average approximation could be established representing the range of effect of tag rotations on RSSI, but this will add unavoidable error the the results of these methods. Most geometric estimation is therefore poorly suited to this problem. The approach presented in [1], where angle of arrival is estimated based on phase change, is the best geometric estimation candidate for this subproblem. Rotations of the tag seem to affect the y-intercept of phase shift against frequency graph, but not the slope. The problem arises when sources of reflections change because of tag rotations. Based on the previous section, we can see that this will have a great negative effect on the estimations on this approach.

The reason that we have chosen LANDMARC over other methods is that it has a solution to each challenge stated above, except for the orientation challenge solved in this paper. LANDMARC requires fixed tag positions as reference points. This paper's algorithms are able to use those reference points to determine rotation differently than other approaches: neural networks can use scattered points, and moving antennas provide different data than required. This solution aims to extend the work of other authors that utilize LANDMARC with a fixed tag rotation so as to allow them to utilize various rotations in conjunction with their improvements.

Chapter 4

Influence of Rotations on LANDMARC

4.1 LANDMARC and Extensions

LocAtioN iDentification based on dynaMic Active Rfid Calibration (LANDMARC), is an algorithm presented in [] that aims to utilize reference tags to comparatively estimate the position of a target tag. First, a reference grid is composed of passive RFID tags at a $1m^2$ resolution. The grid we use is 25 tags in total — 5 tags by 5 tags. Four passive antennas are placed in each corner of the room. Each time that each antenna sends a signal, all of the passive tags reply containing their modulated information. Each of these signals has its own RSSI value calculated via the electrical signal that was reflected by the passive RFID tag. By using reference tags as well as the target tag, we can compute a Euclidean distance between all reference tags and the target tag. By choosing the k-least distances where k is 4, we are able to choose tags that are most likely to be in a similar position as the target tag. We then compute the inverse of the Euclidean distance of these nearest neighbours as a similarity measure. By creating weightings from the similarity measures, we can gain a proportionate estimate for the similarity of the closest neighbours. The final step of LANDMARC is to then compute an estimated target position as the sum of all reference weights multiplied by their respective reference positions.

There are various extensions to the LANDMARC algorithm aim to improve accuracy. One such extension is the Linear Minimum Mean Square Error (LMMSE) estimation technique employed by [3]. In this technique, the authors represent the problem as the linear equation $\hat{Y} = \hat{y}(X) = aX + b$ where X is a matrix of RSSI received by each receiver in the system, a is a scaling matrix and b is a constant. The authors choose a as a function of the covariance matrix of the x-dimension and the cross-covariance matrix of the y-dimension. The authors claim improved accuracy over the traditional LANDMARC algorithm, but state that solving matrices is a limitation of their algorithm because sometimes an accurate parameter estimation for the above equations cannot be found due to non-convergence of iterative matrix solving algorithms. The authors have tested this solution in a matlab environment using the log-distance path-loss model for RSSI to distance conversions, which does not account for rotations and other noise factors that appear in real applications.

Another extension to LANDMARC utilizes an adaptive KNN algorithm. In the original LANDMARC algorithm's k-nearest neighbours component [23], the authors chose to use k=4, which represents the best k-value for most scenarios. The authors stated that this could be due to the square shape of the array of training tags, and that other shapes may require other values of k. Han and Cho [9] describe an approach for adapting the value of k towards a more suitable value for one's particular environment. Before performing the KNN component of LANDMARC, the authors choose the tag with the least euclidean distance to the target tag, and call it the key reference tag. By performing LANDMARC on the key reference tag using a variety of k-values, one can choose the k-value that results in the least distance estimation error. This k-value can then be used in the LANDMARC algorithm in place of the original k=4. Depending on the environment, at different positions different k-values may be observed, which aptly describes the adaptive nature of this approach.

Khan [12] proposes a 3D extension, allowing localisation in all 3 dimensions of space within a room or building. This is performed by introducing a z-value to each equation discussed in LANDMARC. Instead of active tags, the authors decided to use passive tags due to their reduced costs. By utilizing 3D euclidean distances, and a 3D grid of passive RFID reference tags, the authors perform the same K-Nearest Neighbours strategy to estimate the location of a target RFID tag.

It is important to note that our algorithm can theoretically be easily added to these LANDMARC extensions to complement their function, and further improve accuracy. However, in this paper we have not focused on the ability to simultaneously utilize our algorithm as well as the above extensions, but will be a topic of future work.

4.2 LANDMARC Rotation Challenge

LANDMARC is said to solve the challenges of both reflection and dynamic environments, but fails to solve how the rotation of a tag affects RSSI. Although LANDMARC uses active tags, we have found various extensions that use passive tags, but also fail to discuss tag rotation. When using passive tags, rotation of the tag can become a significant factor in localisation, as we will show. Rotations in some axes are worse than others due to polarization, reflections, and energy radiation patterns. Using training data with a rotation different from a testing point generates higher error. We will first discuss the effect of tag rotations to RSSI in more detail, and then present a new approach for resolving the issue of tag rotations in a passive LANDMARC localisation system.

Attempts have been made [7] to quantify what features affect the RSSI of a passive UHF RFID tag. Using an anechoic chamber, as well as an office environment, the authors recorded RSSI values at 3 distances (1, 2, and 3 meters). At each distance, they describe the effect of rotations on each axis of the tag. The antenna used in the study was a circularly polarized, 915MHz antenna. As shown in Figure 4.1, the paper finds that rotations on the X-axis are negligible in the anechoic chamber, but have a slight effect in the office environment. Conversely, the influence of a polarization reception efficiency due to rotations on the Y-axis from -90° to 90° significantly alters RSSI values in both environments as discussed in [7]. The difference in RSSI due to Y-axis rotations is stated to be approximately a second order polynomial. The authors also notes that as distance between the antenna and the tag increases, the angular range of rotations at which a passive RFID tag will respond decreases. Since rotations on the Y-axis greatly affect RSSI readings, and such rotations are the most likely to occur within a 2D localisation system, it is our goal to reduce the impact of such rotations within a 2D system.

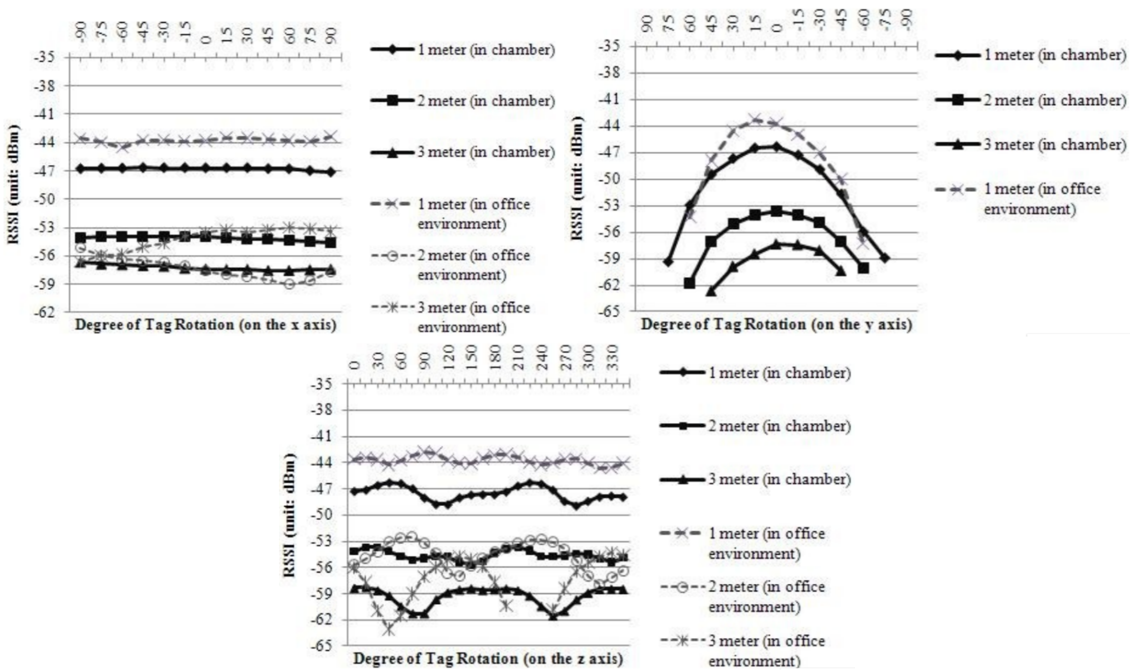

Figure 4.1: Graph of how rotation on each axis affects RSSI value in an anechoic chamber as researched by [7].

Since algorithms that rely on training data must compare new samples to existing ones, we have created a solution to determine how new samples should be compared to existing samples specifically for adding rotations to a localisation system. This is an important topic of discussion, because RFID tags must be placed onto objects to serve a purpose. This means that the back face of the RFID tag will be covered, and line-of-sight to the antenna blocked in that rotation. We also explore the kind of training data that should be collected to create an effective RFID localisation system that includes rotations. By augmenting existing localisation techniques with rotation capabilities, we aim to increase the accuracy of localisation, especially in situations where tagged objects are allowed to rotate freely.

4.3 LANDMARC Rotation Baselines

Before we discuss the new algorithms for solving rotations in LANDMARC, we must create a baseline for comparison. Since we are adding rotational capabilities to LANDMARC, our baseline is the LANDMARC algorithm without rotations. It is useful to define error margins for LANDMARC so that we can compare how well our algorithms perform compared to the original. To show how significantly rotations affect the LANDMARC algorithm, as well as to create this baseline, several different rotations of LANDMARC were performed on the same test data. We classify these rotations as Correct Rotation, False Rotation, Nearly Correct Rotation, and Opposite Rotation.

Let G be the set of grids $G_{1..N}$ such that G_i has a rotation θ_i of $45° * (i-1)$ where $N = \frac{360°}{45°}$. A rotation of 0° describes a tag whose front face has a normal that points north, and a positive rotation describes a rotation on the Y-axis in a clock-wise direction.

Each grid rotation G_θ has a set of reference tags that describe the RSSI at each position. Let each tag in a grid be represented by a set $T_{x,y,\theta}$ where x and y are grid coordinates at the appropriate resolution. If A is the set of antennas, then let $RSSI(T_{x,y,\theta}, A_i)$ represent the RSSI value of $T_{x,y,\theta}$ received by antenna i.

Given any test tag P_k where P is the set of all test tags, we must choose $\Delta\theta$ such that the grid $G_{\theta_{P_k}+\Delta\theta}$ is used to perform LANDMARC on P_k. We then use:

$$(x,y) = LANDMARC(G_{(\theta_{P_{ki}}+\Delta\theta)}, P_k) \tag{4.1}$$

As the LANDMARC algorithm at a specific rotation applied to a test tag, where (x,y) are the coordinates of the estimated location of P_k. By choosing $\Delta\theta$ to be 0°, 90°, 180°, etc, we are able to compare the significance of tag rotation on the estimated coordinates of P_k.

A set of 421 test tags were placed systematically across the grid, with a nearly uniform distribution of rotations. We measured the RSSI value, rotation, and position of each test

Name	$\Delta\theta$	Average Error (m)	Median Error (m)	Std. Deviation (m)
Correct Rotation	0°	1.0	0.9	±0.6
Nearly Correct Rotation	45°	1.2	1.1	±0.7
False Rotation	90°	1.2	1.1	±0.7
Opposite Rotation	180°	1.1	1.1	±0.6
Random Rotation	0° to 180°	1.2	1.0	±0.7

Table 4.1: A baseline of distance errors for LANDMARC using various grid rotations relative to the target tag's true rotation.

tag for use in our experiments. Table 4.1 shows distance error metrics for various $\Delta\theta$ values.

We can see in Table 4.1 that as the angle difference increases towards 90° we gain larger average errors in our location estimation, as well as higher standard deviation. At 180°, the tag's back is again facing the antenna, and provides less error than 90°. Since a passive RFID tag reflects outwardly from both of its faces, this result is expected. We can see that it has higher error than 0°, which is most likely because our RFID tag has a cardboard backing that helps secure it to the apparatus used to conduct the experiment. This cardboard absorbs some of the radio signal, thereby weakening the received signal in that direction and reducing our accuracy.

4.4 Related Works

Some localisation algorithms utilize various sensors in addition to RFID tags to gather more information about the possible orientation of the tag. These sensors could be accelerometers, temperature, camera, magnetic field, motion, etc. Although not RFID, [10] aims to utilize most devices found on smart phones to improve localisation accuracies of the device. Likewise, [11] utilizes an accelerometer to localize an active RFID tag without any reference tags by broadcasting the accelerometer data to a system that can calculate the next position of the tag based on acceleration values. These values could help determine additional information such as tag orientation. Since our system will utilize low-cost, off-the-shelf passive RFID tags that have no dedicated battery, and no on-board CPU, such external modules are not valuable for our situation.

Lim, Choi, and Lee [17] describe how a grid of passive tags, similar to LANDMARC, can be used to estimate the position, and even orientation of a mobile robot. This is done by using a moving antenna stationed on the bottom of the mobile robot, and continuously estimating the movement of the robot using position, and orientation data. We recognize the benefits of moving an antenna to find additional information about the system, but desire a stationary system to keep overall costs, and system maintenance low.

Chapter 5

Solving Rotation Challenge via Rotation Dimension Reduction

5.1 Solution Inspiration

Our research started with the various factors associated with RFID RSSI for localisation, as well as the established algorithms discussed in recent papers on the topic. Each algorithm that we found while performing a survey of the state of the art of RFID localisation attempted to solve some or most of the challenges that we have discussed in Section 3.4. A common problem in all of the algorithms is that they are not specifically designed to solve tag rotations, nor did the papers discuss how tag rotations affect the results of their systems. We then made it our focus to determine how to utilize tag rotations to improve most existing RFID localisation systems.

LANDMARC is one of the algorithms that solves almost all challenges that we had categorized, except for the tag's rotation. By applying our algorithm for reducing the effects of rotation on localisation to LANDMARC, we allow LANDMARC to solve all challenges that we have discussed. By sacrificing set-up time, multiple grids were created at various rotations that could allow us to augment the LANDMARC algorithm to include the rotation dimension empirically. By having a hands-on application, we were able to test many ideas to see how they performed with LANDMARC. The ideas we derived were:

1. To predict the rotation, then utilize the same rotation training data when performing comparisons. We constructed various algorithms for trying to predict the rotation of a tag, with only some being successful.

2. To aggregate each position's rotations, thereby creating a single grid of training data. This approach by far had the most success.

By seeing how LANDMARC was affected by the strategies, we will be able to abstract the solution to other localisation algorithms that utilize a comparison between new samples and training samples. We determined that Rotation Dimension Reduction via Average was a great solution for not only adding rotations to a localisation system, but to also reduce the effects of reflection and line-of-sight obstruction by utilizing more information about the environment via rotations of the training samples. We discovered why comparing an average of rotations outperforms a 100% perfect rotation prediction system, and consider how it might be applied to other localisation techniques.

5.2 LANDMARC Rotation Extension Algorithm

Our algorithm extends the LANDMARC algorithm [23] by including the ability to rotate a tag by any Y-axis degree, and gain more accurate results than the original system due to the additional training information required by our algorithm. We utilize extra rotational training data to perform a more accurate version of the k-nearest neighbours algorithm usually used by LANDMARC. We do this by decreasing the error margin of a comparison between a newly read tag, and each training tag. This is performed by reducing the total variance of the comparison by aggregating the rotations of tag training data.

The first step of our algorithm requires that one trains multiple grids in addition to the single grid required by LANDMARC. Each grid should be trained at incremental steps θ, such that the total amount of grids created will be $Number\ of\ Grids = \frac{360^\circ}{\theta}$. For our empirical results, we have chosen a resolution of $\theta = 45^\circ$, and postulate that lower resolutions will be of little statistical significance relative to the amount of effort required to gather the training data. For algorithms using statically placed tags, we suggest using multiple tags surrounding the grid point of interest, one at each degree interval. This approach could introduce tag-to-tag collision interference [5]. Figure 5.1 is an example of our final LANDMARC grid where each square is a reference tag, and each arrow is a rotation.

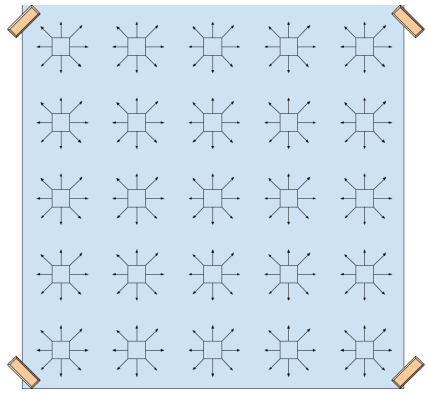

Figure 5.1: A 4 meter by 4 meter LANDMARC grid trained at 8 different rotations.

Once the training grid is established, we can create a single grid by aggregating the data at each tag location. We describe a tag location as $T_{x,y}$ where x describes the column position of the tag, and y describes the row position at any desired grid resolution, such that the top left corner of the grid is (0,0). We have used a grid resolution of 1 meter by 1 meter such that each meter in either dimension describes a tag position as per LANDMARC [23]. Let $R_{x,y,\theta}$ be the RSSI value of a passive RFID tag at position (x, y) with a rotation θ. We then define our single, new aggregated grid to be:

$$R_{x,y} = \sum_{\theta=0}^{360^\circ - \Delta\theta} \frac{R_{x,y,\theta}}{360^\circ/\theta} \tag{5.1}$$

Using our new M x N grid, we perform the LANDMARC algorithm on any newly read RFID tag at any estimable position (x,y) where $0 \leq x < M, 0 \leq y < N$, and rotation θ such that $0 \leq \theta < 360^\circ$. More specifically, given a new tag's RSSI data $T_{x,y}$ where x and y are bounded by the training grid's minimum and maximum values of x and y, we estimate its 2D position. This is done by first calculating the euclidean distance from T to each existing $R_{x,y}$. The 4 lowest distance calculations are then chosen as our nearest neighbours. The neighbours are denoted as $L1_{x,y}$ to $L4_{x,y}$ in increasing order of distance. Let MIN(n, D) be a function that chooses the n least amount of values from a set D. The distance between two tags is defined in terms of the RSSI value of each antenna A_i. We formally state the above as: n

$$RSSI\_DISTANCE(T1,T2) = \sqrt{\sum_{i=0}^{|A|} RSSI(A_i)^2} \tag{5.2}$$

$$L(T) = L1..L4 = MIN(4, \{RSSI\_DISTANCE(T, L_{x,y}) | x \in \{0..M-1\}, y \in \{0..N-1\}\}) \tag{5.3}$$

We use L1..L4 in Equation 5.3 as landmark points that each help to position a newly read instance. We calculate the desired tag's position by taking the inverse of the euclidean distances, which creates similarity values labelled S1..S4 respectively. Each similarity value divided by the sum of all similarity values acts as a weight, becoming W1..W4:

$$S_n = \frac{1}{R_n^2} \tag{5.4}$$

$$W_n = \frac{S_n}{\sum_{i=1}^{n} S_i} \tag{5.5}$$

We then perform an expected value calculation in each dimension (x and y) independently, thereby creating an estimated position of our new tag. Let P1..P4 in Equation 5.6 denote the positions of tags 1 to 4 respectively. We formally define the expected position as:

$$E_{x,y}(T) = \sum_{i=1}^{n}(W_i * P_{i_x}, Wi * P_{i_y}) \tag{5.6}$$

The estimated position of the new tag is thusly obtained, using a k-nearest neighbours algorithm applied to a training grid. Four nearest neighbours are chosen, which utilizes the euclidean distance of RSSI values among all antennas as weights in an expected value calculation. The expected value is calculated independently for both x and y dimensions. There exists the possibility that the $RSSI\_DISTANCE(T1,T2)$ could be 0 if two tag readings are exactly the same, which is a problem due to the algorithm taking the inverse of the RSSI distance. Although this is a highly rare case due to the number of readings taken, and various fluctuating sources of interference, it must be considered. We recommend simply re-scanning the tags in this case due to its unlikliness.

5.3 Rotating Tag Comparison for Machine Learning

LANDMARC training data that uses multiple rotations allows more information to be gained about the environment, but using that information to improve the accuracy of localisation may not be intuitive. Here we describe the way in which training data of multiple rotations can be used to localise a single rotation target passive RFID tag more accurately than without rotations. To add rotations to LANDMARC, we must devise a method of comparing a newly read passive RFID tag with an RSSI value per antenna, to existing landmark training tags that have an RSSI value per antenna, per rotation. Both of these methods of comparison aim to improve the accuracy with which new RFID tag readings are compared to training readings, therefore improving accuracy of machine learning algorithms, such as the K-Nearest Neighbours algorithm used in LANDMARC.

Rotation Dimension Reduction

This comparison requires a reduction in dimension of landmark training tags, to the same dimension as our newly read tag. This means reducing the rotation portion of our training data via an aggregation function. More formally, given a newly read tag $T_t \in (R, \theta_{T_t})$ where θ_{T_t} is an unknown rotation of the newly read tag, and $R(T) = RSSI(T,a)|a \in A$ for an array of static antennas A. Let $a : [(R,\theta)] \to R$ be an aggregation function of a list of rotation and RSSI list pairs, and $d_1 : R, R \to \Delta R$ be our comparison function between two RSSI lists to produce a single RSSI difference value. An example of this can be seen in Figure 5.2.

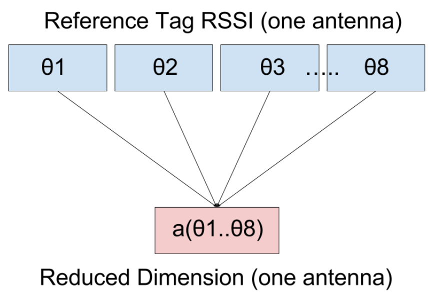

Figure 5.2: An example of dimension reduction on a reference tag's RSSI at one antenna, with 8 different rotations.

We describe rotation reduction of a particular (x,y) position as placing one horizontal line per antenna across the graph of rotation versus RSSI value. These horizontal lines represent the result of the aggregation function being applied to each antenna over all rotations, and is used to conduct a comparison to a newly read tag in the form of a distance calculation.

In our experiments, we perform a rotation reduction using the mean as an aggregation function. More specifically, let T_{x,y,θ_t} be a training tag at grid location (x,y), and rotation θ_t. Our aggregation function then becomes $a(T_{x,y,\theta_t}) = \frac{\sum_{\theta=0}^{360-\Delta\theta} T_{x,y,\theta}}{360/\Delta\theta}$ where $\Delta\theta$ is the angle resolution of the training data.

Rotation Dimension Abstraction

Alternatively, instead of reducing our training data by aggregation to match the known dimensions of a newly read tag, we could estimate or abstract a value of the target tag's rotation. This would allow our newly read tag to match the dimensions of the known training data. We then define a comparison function $d_2 : (R,\theta),[(R,\theta)] \rightarrow \Delta R$ to compare a newly read tag to a list of landmark training tag rotations. This process is shown in Figure 5.3.

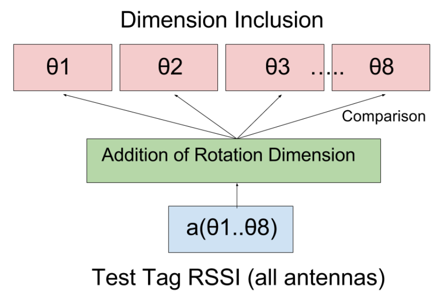

Figure 5.3: An example of dimension abstraction on a newly read test tag with a single rotation, and comparison function on reference tags at multiple rotations.

We have implemented an example of Rotation Dimension Abstraction comparison by trying to predict the rotation of the newly read tag. The prediction algorithm utilizes all LANDMARC training data as well as the data of the newly read tag, and chooses the LANDMARC grid with the rotation that results in the lowest variance after LANDMARC KNN with k=4.

5.4 KNN Performance

One of the most important factors of our research topic is the comparison of one newly read sample to a training sample. By improving the accuracy of an algorithm's comparison to training data, the algorithm can more accurately determine location. This is true of the k-nearest neighbours algorithm that LANDMARC uses, as well as neural networks that rely on training data to statistically compare new samples.

A tag with a normal perpendicular to an antenna results in more energy loss, therefore a lower RSSI value. It can be seen by both the research of [7], as well as our own samples, that the RSSI value fluctuates sinusoidally with rotation. Our own samples show great sources of interference, reflection and/or obstruction at particular rotations due to our

Name	Training Data	Mean Distance From T_t (m)	Std. Deviation (m)
8 Rotation Grids	8 grids x 25 tags	2.0	± 1.0
(RDR-Avg) Grid	1 grid x 25 tags	1.7	± 0.8

Table 5.1: Comparing distance error and variance of KNN algorithm between rotation dimension reduction and all 8 rotations.

experiment environment. It is these fluctuations that cause inaccuracy during the comparison of a particular rotation to another tag at the same rotation. This is because two different tag positions at the same rotation can have different sources of reflection, obstruction, or interference.

There are three types of comparison that we can perform in a localisation system that includes rotations. We can perform a) one-to-one rotation, b) one-to-many rotations, or c) one-to-aggregate rotation. The reason we have to compare one rotation to other possibilities is that a newly read sample only contains the information of a single rotation, whereas training data contains data for multiple rotations. We gain statistics from these comparisons that lead to a conclusion about which type results in a more accurate comparison. Variance, and standard deviation are our measures of choice as they describe how much difference exists within our comparisons. We can more accurately compare any two tags by choosing the comparison type with the lowest variance.

The reason that Rotation Dimension Reduction has a lower variance lies within the fact that two of the same rotations at different positions can have very different RSSI fluctuations due to the causes we have discussed. If one particular rotation of a newly sampled tag has an unidentifiable fluctuation in RSSI, each comparison type handles that fluctuation differently. One-to-one performs such that both tags may have fluctuations, one tag may have them, or neither. One-to-many compares incorrect rotations, and therefore increases the potential of comparing inconsistent fluctuations, thereby increasing variance. One-to-rotation compares a rotation to the average of all other rotations. The average of all other rotations decreases the effects of fluctuations by aggregating them. This comparison provides the least amount of variance due to its decrease in the effects of fluctuations.

Using our 8 rotation LANDMARC grid, as well as 421 test tag (position, rotation) pairs, we measured the performance increase of the KNN algorithm when average of rotations is used, as opposed to comparing a test tag to all possible (position, rotation) pairs. In our case, a comparison is taken as the Euclidean distance of RSSI values from any number of antennas, as discribed in the LANDMARC algorithm. In Table 5.4 we show the mean distance error of chosen tags from KNN, as well as the standard deviation of their errors. We conclude from these results that while averaging rotations, the K-Nearest Neighbours algorithm more consistently finds tags that are closer to the target test tag. This allows a more accurate estimation of a target tag's estimated position based on KNN tag similarities.

Chapter 6

Rotation Dimension Reduction on LANDMARC

6.1 Equipment

A passive RFID system requires one or more passive RFID tags, one or more passive RFID antennas, as well as one or more RFID antenna routers. In our passive RFID system, we use a 53mm RFID tag from SMARTRAC [33] called Frog 3D (MONZA 4D) that operates at a frequency range of 860-960 MHz. We use a circularly polarized passive RFID antenna from LAIRD [4] called Laird PAL90209H that operates at a frequency range of 902-928 MHz. We also use an antenna router from Motorola [31] called FX7500 that controls up to 4 passive RFID antennas. The router sequentially operates each antenna separately so as to avoid intereference, and also controls frequency hopping between 50 different frequencies in the band to both avoid intereference, as well as conform to unlicensed Canadian electrical signal laws.

All programs used in the experiment were written the programming language C#, and compiled and run on the Windows XP operating system. The Motorolla Enterprise Mobility Development Kit (EMDK) was used to interface the computer with the RFID antenna routers. This allows us to query the routers for information retrieved from the RFID antennas such as tag Electronic Product Code (EPC), phase shift, RSSI, time collected, antenna ID that collected the information as determined by the router, and binary data stored in the tag's limited memory. It is with this equipment and information that we have conducted our experiments.

6.2 Experiment Setup

Since LANDMARC is the algorithm that we are extending, our experiment environment should be similar to previous LANDMARC research. In a 7m by 10m space with concrete walls, and floor, and a metalic ceiling, a 4m by 4m grid is created with a 1m square resolution. We placed our antennas approximately 5 meters off the ground, nearly at the ceiling. The antennas are located at each corner of the grid, and pointed towards the center of the grid. We attached the tag to a metal apparatus that stands approximately 1.5 meters from the ground. A few tables are present in the grid such that they do not affect line of sight from the tag to the antennas, even though this is shown by previous LANDMARC research not to be a significant factor [23]. Special apparatuses were created to keep a constant height where tables exist.

LANDMARC requires passive RFID tags to be placed at each cross-section of the grid as reference tags. The idea of LANDMARC is that two tags that are sufficiently close to each other will be affected by the same environmental factors [23]. However, since our experiment's environment is static, we have no need to worry about such dynamics. Therefore, we decided to create virtual reference tags to both reduce the number of RFID tags required to perform the experiment to just one. As well, this allows us to disregard any error that may be created by comparing the data of two differently constructed RFID tags. Even though our experiement is performed virtually, our algorithms can also be utilized within a LANDMARC system that has physical reference tags, thereby regaining the dynamic environment solution that the original LANDMARC algorithm offers.

Since our goal is to eliminate rotational error, we have to train LANDMARC at not only a single rotation as in the original LANDMARC algorithm, but every rotation within a certain rotational resolution. Just as LANDMARC has a grid resolution parameter, in this case 1m, we also have a rotational resolution parameter, in our case 45°. It is postulated that a finer resolution than 45° will result in no significant benefits, and will require too much training data to be feasible in a real world application.

6.3 Experiment Results

Our experiments consist of 421 test tags in a LANDMARC system that has training data of 8 total passive tag reference grids of differing rotations equally spanning 360°. We measure performance as a distance error using the Euclidean distance function from estimated position to true position. We formally state error as a function of the target tag T to its estimated position using:

$$Distance(T1,T2) = \sqrt{(T1_x - T2_x)^2 + (T1_y - T2_y)^2} \tag{6.1}$$

Let T_t be the newly measured target tag and $T_{estimated} = LANDMARC(T_t, G_{RDRAvg})$

$$Error(T) = Distance(T, T_{estimated}) \tag{6.2}$$

[htbp] Name	$\Delta\theta$	Average Error (m)	Median Error (m)	Std. Deviation (m)
Correct Rotation	0°	1.0	0.9	±0.6
Random Rotation	$0-180°$	1.2	1.0	±0.7
RDR-Average	N/A	0.9	0.8	±0.6

Table 6.1: A comparison between LANDMARC baselines and Rotation Dimension Reduction using Average as an aggregation function.

Our results in Table 6.1 clearly show an improvement over both the Correct Rotation, as well as Random Rotation results. This is an unexpected result, as our hypothesis was that a LANDMARC system that could accurately detect and use the same rotational grid with 100% accuracy would serve as a lower bound for accuracy using such a system. Our Rotation Dimension Reduction via Average shows that this is not true, with a 10% relative improvement of average distance error over the theoretical perfect-rotation detection LANDMARC system. Since a perfect-rotation detection system has not yet been constructed, and benchmarks for adding rotation to a LANDMARC localisations system have not been established, we use a baseline of the naïve implementation for comparison. It makes sense to use such a baseline in practical applications as objects that are being tracked are usually rotating in at least the Y-axis, and therefore a LANDMARC system will have to perform with such objects. Rotation Dimension Reduction via Average has a 20% relative improvement in average distance error over the rotation-naïve baseline.

It seems unintuitive that by aggregating incorrect rotations of training tags, one can perform more accurate localisation on average than selecting a grid of the true rotation of a test tag. Although unintuitive, we explain in Section 5.4 that the aggregation reduces RSSI fluctuations caused by line-of-sight interference, reflections, and even rotations themselves. This allows for a more accurate comparison of test tags to training tags, as shown by the reduction of a standard deviation. This reduction in standard deviation allows us to find more relevant reference (landmark) tags for use in machine learning algorithms.

These empirical results serve as a demonstration of our technique for handling a freely rotating passive RFID tag in a localisation system. We expect similar results for other algorithms where tag training data is required, such as for other statistical or machine learning techniques like neural networks, or bayesian methods.

Chapter 7

Conclusion

We have discussed an application of our thesis by applying it to the LANDMARC algorithm for localisation of RFID tags. By reducing the dimensions of RFID systems such that we eliminate the rotation dimension, we can reduce the amount of noise introduced by this dimension. This is in part due to the periodic nature of the rotation dimension of RFID tags as described by our thesis. By reducing the dimension of training data for any periodic dimension for which a newly read instance exists at only one value in the period, we can more accurately compare the new instance to the reduced training data, thereby improving machine learning algorithm accuracy applied to the data.

In our experiments, we utilized an aparatus made of metal to raise the passive RFID tag above the ground at a constant height. We also used a cardboard backing that helped secure the RFID tag to the aparatus. Since a passive RFID tag must be placed onto an object for an identification or localisation system to serve a purpose, we wish to experiment with the effects of changing the material and size of the object to which the tag is attached. Being secured to different objects will affect the ability of the tag to reflect signals on the attached side. It is also possible that different training data may be required to accomodate the type of object that the tag is secured to, requiring further research.

When comparing a newly read tag to our training data, we should aggregate our rotation data to allow appropriate comparison to a single-rotation RSSI reading. This paper studies the simplest function for aggregating rotational data, whereas other functions for aggregation should be researched such as the RSSI value that results in the Minimal Mean Square Error (MMSE). Which function works best may depend on the type of material, and size of the object to which the tag is attached. Both of these ideas should be explored to improve performance.

In this paper, we focused on the Y-axis of rotation, meaning rotation about the ground's normal axis while the face normal of the tag is orthogonal to this axis. This axis was chosen because object's mostly reside ”upright” while tracking is desired, and therefore will never rotate in other axes. It may be worth researching other axes of rotation for tracking objects that can rotate freely, and especially for tag localisation in 3D space.

Our solution to the rotation problem for RFID localisation is an unintuitive one because our solution utilizes false rotations of an RFID tag to assist in position estimation. This works because each rotation consists of inherent noise due to the environment. We reduce this noise by aggregating the training data at various rotations per training position to create training data that has a less noisy RSSI, and therefore represents its position in the environment better than using data of a single rotation.

Multiple extensions to LANDMARC have been listed in Section 4.1. Each of these extensions, like ours, aim to improve accuracy while optionally adding increased utility to the original algorithm. We plan to research how Dimension Reduction of LANDMARC Rotations can be implemented alongside existing LANDMARC extensions, and how it affects accuracy of the system. Our algorithm adds a rotation dimension to the LANDMARC localisation problem, and then solves it, allowing it to be modular enough to implement into existing extensions.

There is a lack of research on how considerations of passive RFID tag rotations can improve RFID localisation algorithms. In this paper, we improve the accuracy of machine learning localisation algorithms by means of Rotation Dimension Reduction. We have also identified another method of tag comparison that we call Rotation Dimension Abstraction, but do not explore its potential capabilities or limitations. We apply rotation dimension reduction to the LANDMARC algorithm to empirically show its benefits, and gain a 20% relative increase in accuracy. There are many topics of future work that can expand on the ideas that we have presented in this paper, and can potentially generate even more accurate results.

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Appendices

Appendix A - Additional Results

In addition to the data given in Figure 4.1, we have also computed the skewness and kurtosis of our data for further insight given in Figure 7.1.

Name	$\Delta\theta$	Std. Deviation (m)	Skewness	Kurtosis
Correct Rotation	0°	0.57	0.82	0.43
Nearly Correct Rotation	45°	0.68	0.82	0.45
False Rotation	90°	0.73	1.04	1.38
Opposite Rotation	180°	0.61	0.77	0.18
Random Rotation	0° to 180°	0.68	0.85	0.49
RDR-Average	N/A	0.59	1.23	2.00

Figure 7.1: Features of the distance error distribution for LANDMARC using rotation dimension reduction, as well as various grid rotations relative to the target tag's true rotation.

We have also gathered data on how far away the estimated position of each tag is from the center of the grid. This is because it is thought that the LANDMARC algorithm pulls estimations towards the center of the grid. We wanted to see how our method compared in this aspect. The following values are retrieved from running 421 test tags through the LANDMARC algorithm, and calculating the Euclidean distance from the center of the LANDMARC grid.

Name	$\Delta\theta$	Avg. (m)	Std. Deviation (m)	Skewness	Kurtosis
Correct Rotation	0°	1.28	0.53	-0.20	-0.77
Nearly Correct Rotation	45°	1.26	0.52	-0.08	-0.95
False Rotation	90°	1.27	0.53	-0.19	-0.93
Opposite Rotation	180°	1.27	0.52	-0.06	-0.85
Random Rotation	0° to 180°	1.29	0.54	-0.22	-0.92
RDR-Average.	N/A	1.55	0.54	-0.49	-0.74

Figure 7.2: This is a comparison of the distance error distribution of estimated positions from the center of the LANDMARC grid. The true average distance from the center for our 421 samples was 1.7 meters.

Appendix B - Equipment

Here are images depicting the equipment that we have used to conduct our experiments.

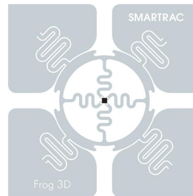

Figure 7.3: The passive RFID tag that we have used in our experiments [33].

Figure 7.4: The passive RFID antenna that we have used in our experiments [4] [30].

Figure 7.5: The passive RFID antenna router that we have used in our experiments [31].

Vita Auctoris

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