Deriving Activity from RFID Detection Records in an Assisted Living Context

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List of Abbreviations and Acronyms

AIMD:	Additive-Increase/Multiplicative-Decrease
ANSI:	American National Standard Institute
CAM:	Customer Access Matrix
CBMG:	Customer Behaviour Model Graph
CEPT:	European Conference of Postal and Telecommunications Administrations
CTM:	Customer Transaction Mining
DAT:	Discussion Analysis Tool
EAS:	Electronic Article Surveillance
FDA:	Food and Drug Administration
GPS:	Global Positioning System
HF:	High Frequency
ISO:	International Organization for Standardization
LANDMARC:	Location Identification based on Dynamic Active RFID Calibration
LF:	Low Frequency
MCC:	Markov Chains Cluster
MS:	Microsoft
MTIS:	Material Tracking Information System
PS:	Peres-Shields Estimator
RFID:	Radio Frequency Identification
SDK:	Software Development Kit

SMURF:	Statistical sMoothing for Unreliable RFID Data
SNR:	Signal-to-Noise Ratio
UHF:	Ultra-High Frequency
VBR:	Variable Bit Rate
VLMC:	Variable Length Markov Chains
Wi-Fi:	Wireless Fidelity
WISP:	Wireless Identification and Sensing Platform
WLAN:	Wireless Local Area Network

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature: ______________________

Michael Zheng

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Abstract

There has been a significant growth in the deployment of Radio Frequency Identification (RFID) in the supply chain in the recent years. Since RFID requires less cost and infrastructure than the sensor networks such as Ultrasonic or Wi-Fi, it has been applied in many business and research domains. The major applications of RFID technology include location position, object tracking and activity monitoring. Particularly in the individual activity monitoring circumstance, it is expected that by detecting the object with which the person interacted, the related personal movement is able to be recognized. However, the inherent unreliability of RFID data results in the uncertainty of the RFID detection of activity.

This research estimates the accuracy of using RFID detection records to monitor personal activity in an assisted living context. The methodology for this research is a quantitative approach by using design science. Two real experiments are conducted for performing activity monitoring in a laboratory environment. Both experiment results show that false positive reads have a serious influence on the accuracy of detecting individual motion. In order to remove the noisy data from the original RFID data stream, the multi-level data pre-processing method is used and analysed in the research. The cleaned dataset shows the perfect accuracy of personal activity inference. Although this proposed method is efficient for filtering the noisy data and predicting the correct individual movement in this research, it only focuses on recognizing the regular personal activity in a clean indoor environment. Due to the complexity of human indoor behaviour, future exploration needs to be carried out in other different environmental backgrounds.

Chapter 1

Introduction

Radio Frequency Identification (RFID) is defined as a technologic method that is applied to automatic identification. With the rapid growth of interest in RFID, many industries have adapted to adopt this new technology in operating the business. Research carried out by Sarma et al. (2000) indicated that RFID was set to revolutionize industrial control as it holds the potential to simplify and make more robust the tracking of parts or part carriers through manufacture, storage, distribution and ultimately the supply chain. Especially in the supply chain, the RFID technology tangibly benefits on the supply, operation and distribution levels (Angeles, 2005). In the real world deployment, RFID technology has been integrated into the warehouse management (Kalischnig, 2004), baggage control in the airport environment (Sagahyroon, 2007), and even in the sports domain such as tracking athletes at marathons (RFID Gazette, 2004). The most remarkable commercial RFID application is considered to be the implementation of RFID system in the Wal-Mart supper market in the USA. By using the RFID system, Wal-Mart was estimated to save billions of dollars from tagging the products (IATA, 2005).

Besides the application in the business practice, RFID is also able to assist the people in a living context. It offers a potentially flexible and low cost method of locating object and tracking people within the buildings. Kulykin et al. (2004) stated that RFID can be used in a robot-assisted indoor environment and to guide people to avoid the visually impaired barriers within the building. Moreover, RFID can be applied in the health care domain, For instance, it was also used in monitoring the elder people activity by placing RFID systems in different rooms of a house (Yeager et al., 2006). In addition, RFID tools may be useful to support blind and partially sighted people with daily living activities and assist in the rehabilitation of adults with acquired brain injury (Parry et al., 2007).

On the other hand, integrating sensor technology in the daily environment, several issues are essential for the end user to have a consideration. For instance, the results generated by the sensor in a wide range environment should be reliable. The sensor should be robust and user identification should be easy to achieved (Korhonen et al., 2003). Furthermore, Jeffery et al. (2007) stated that the inherent characteristic of sensor data such as unreliable and low level results in the difficulty of being used directly by applications. As a class of sensor technology, the reliability of RFID data generated by the RFID system should be evaluated before implementing the system for assisting the person in a daily living context.

1.1 Research Objective

The aim of this research is to derive activity from RFID detection in an assisted living context. Therefore, the main research question is stated as: how can RFID detection sequences be cleaned to infer activity? In order to achieve research this objective, a number of literature sources regarding the areas of RFID technology, application, activity monitoring, and data management are explored. Moreover, the real experimental measurement is conducted to examine the research hypothesis. In addition, appropriate algorithms are used and analysed in an attempt to solve the research question.

1.2 Research Contribution

The main contribution of this research study could be in two areas:

1) Academic Literature: The research and the literature review would add to the body of academic studies. This research will be a valuable contribution to evaluate the accuracy of using RFID data sequence for personal motion inference in an indoor environment.

2) RFID Application Development: The research could provide the possible solution on the role of the method for filtering RFID data and the model for reorganizing individual activity. This would be valuable information for the future RFID application development.

1.3 Research Structure

The structure of this research is organized by seven chapters, which starts from the chapter of introduction, and then goes through chapters of literature review, research methodology, through chapters of experiment design and result, data pre-processing and analysis, discussion and future work and ends by the chapter of summary and conclusion. The overview of research structure is shown in Figure 1.1.

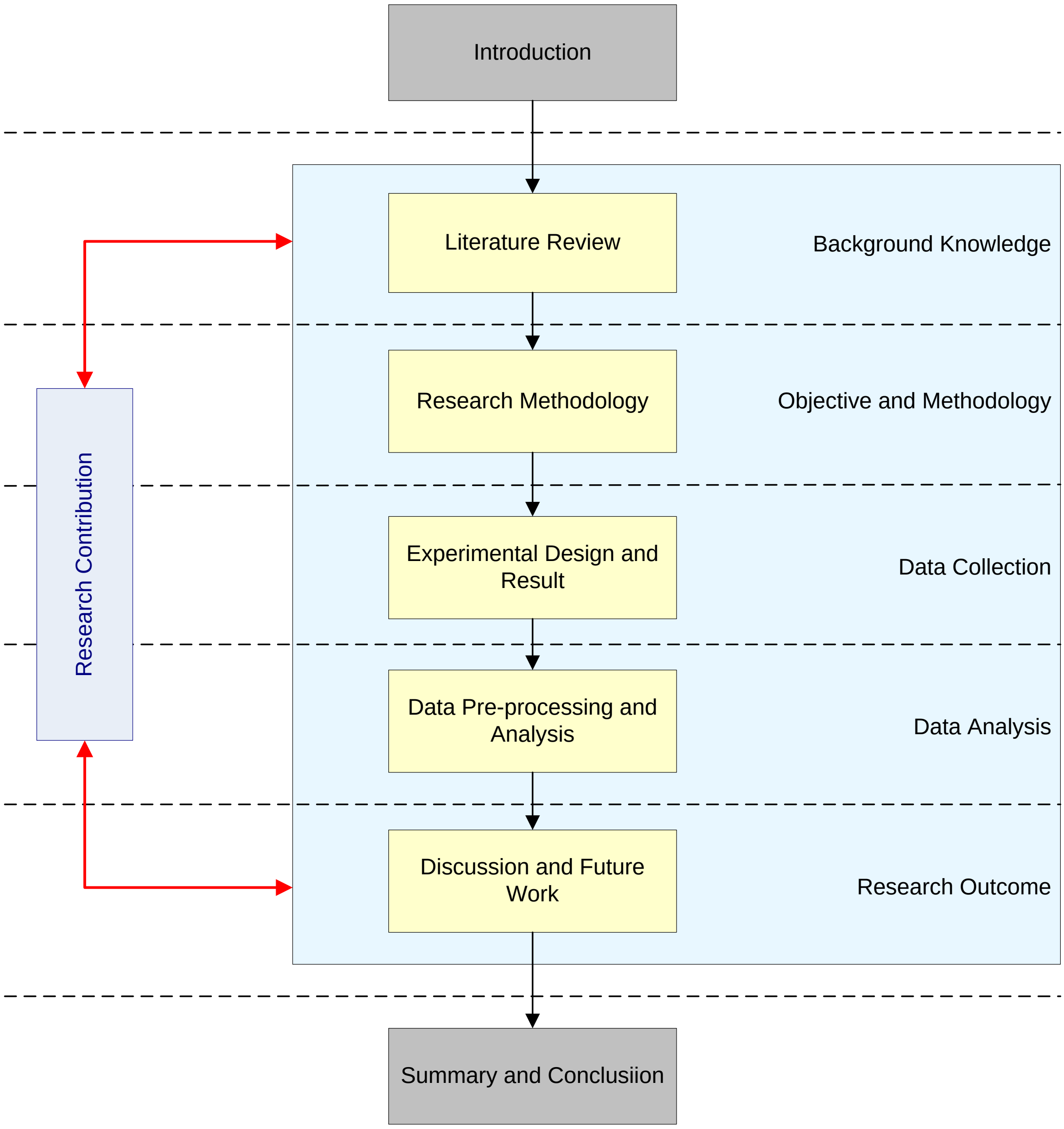


Figure 1.1: Research Structure

The Literature review (Chapter 2) describes the background knowledge of RFID technology, system infrastructure and major applications. Chapter 3 however, reviews the research objective and carries out the research methodology, with a comparison of two frequently used experimental measurements. On the other hand, Chapter 4 covers the process of data collection in this research by using the RFID system to conduct two real experiments. Data analysis in this research is carried out by Chapter 5 where the original data collected from experiments is pre-processed and analysed. Furthermore, the research outcome is presented in Chapter 6 by the discussion of data analysis as well as the future work. Last but not least, Chapter 7 concludes the research outcome as well as summarizing all of the previous chapters.

Chapter 2

Literature Review

This Chapter provides an in-depth view on the area of the development of RFID technology including the infrastructure, frequency range and standard. It also presents the major use of RFID technology in an indoor environment. In addition, most papers reviewed in this part come from five online databases, which are IEEE Xplore, ACM Digital Library, Science Direct Journal, Springer Journal and Google Scholar.

2.1 RFID Technology

Radio Frequency Identification (RFID) Technology is a term referring to the use of wireless devices to detect radio frequency signals and record the data transferred from a group of sensors (McCathy et al., 2002). Nowadays, it is specified as a group of technologies that is applied in the area of automatic identification for people or objects. The most common use of this application is to associate the unique RFID tag with persons or objects (AIM, 2008). The following section briefly describes the development of RFID technology.

2.1.1 Brief History of RFID

Interest in RFID was inspired by the radio broadcasting and radar research undertaken during the Second World War. One of the earliest landmark papers of exploring RFID was published in 1948 by Harry Stockman, which stated that problematic issues of reflected-power communication had been solved and some useful application had been explored (Kulkarni et al., 2006). The technology was further developed in 1950 and 1960. One typical application in this era was the implementation of sensormatic and checkpoint system: electronic article surveillance (EAS) in some companies. In 1970s, interest in developing RFID application was spread, globally, to many academic institutions such as Los Alamos Scientific Laboratory, Northwestern University and the Swedish Microwave Institute Foundation. The wide deployment of RFID application began in the1980s while the interest varied in the Europe and the USA. In 1990s, RFID technology had a significant impact on electronic toll collection around the world. The development and adjustment of integrating circuits were also underway during that timeframe to reduce the microwave RFID tags to a single integrated circuit (Landt, 2005).

RFID technology swept many industries world wide over these decades. In the 21st century, the technology is becoming ubiquitous to both academic institutions and business industries. At the same time, numerous RFID applications are well developed in order to serve end users. However, there are still several uncompleted works that are considered by both researchers and vendors, such as allocating frequency spectrum between countries, developing a global standard, and introducing commercial applications (Roberts, 2006).

2.1.2 RFID System Infrastructure

A RFID system consists of three typical components, which are RFID tags, RFID tag reader with an antenna plus a transceiver, and a host system that stores RFID data transferring between reader and tags (See Figure 2.1). The detailed description of each component is listed as follows:

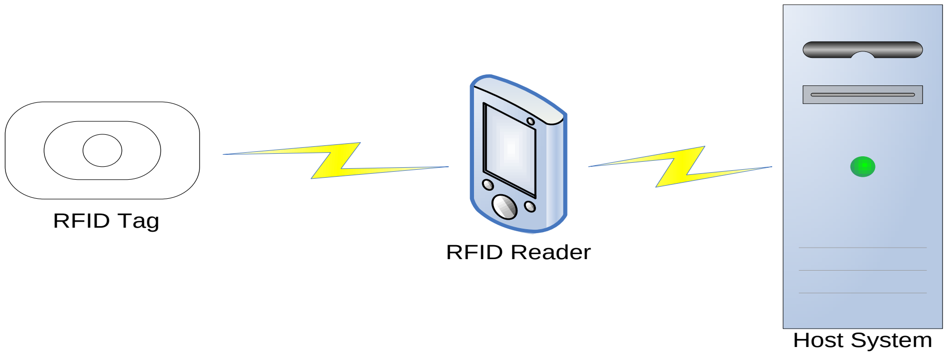


Figure 2.1: Typical RFID System

RFID Tag

RFID tags contain two major parts which are integrated circuit and antenna. The integrated circuit is a microprocessor chip whereas the antenna is responsible for defining the reading range of the tag (See Figure 2.2). RFID tag is activated to be read and written by the emission of radio signals from antenna. It can be defined in several categories according to a range of parameters and criteria (Robshaw, 2006). Depending on the data storage capability, RFID tags are distinguished as Read-Only and Read/Write Tags. Read-Only tags have a unique ID attached to them without the function of storing data in the tag which is why they are usually used to represent the tagged object in conjunction with a database (Bassi, 1996).

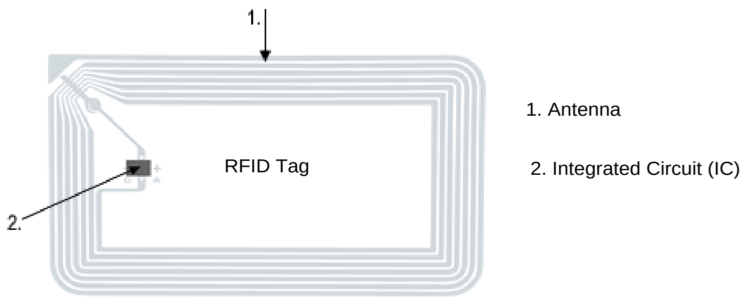


Figure 2.2: The Structure of RFID Tag (UPM RAFLATAC, 2008)

On the other hand, RFID tags are also classified as two categories; active tags and passive tags by many researchers (Nagi et al., 2008 & Robshaw, 2006 & Roberts, 2006). Active tags have a built-in power supply, which do not require the external electromagnetic interaction of RFID reader in order to radiate. Passive tags can only be activated by the electronic waves generated from RFID reader. In other words, they will only function when powered by a nearby reader. The shorter reading range of passive tags requires higher power reader to communicate with it, which may reduce the RFID performance in an electromagnetically noisy environment. However, passive tags are cheaper, lighter, and smaller than the active tags. Besides these, there is also another class of RFID tags called semi-passive tags. This kind of tags contains some properties of both passive and active tags. Similar to the active tags, the built-in battery enables tags to perform some active functions such as temperature logging. Then again, these particular types of tags can also be activated by response to radio frequency energy when communicating with the reader. Compared with passive tags, although semi-passive tags are more expensive, they better support data storage and vary in shape, sizes and protective housings (Garfinkel & Holtzman, 2005).

Due to all of the different features of these three tags, they are able to be applied in diverse applications. Despite the fact that most active tags can be read and written, they are usually expensive and big. Passive tags require an external radio wave to get active, but they are much more affordable and compact in comparison to active tags. Semi-passive tags not only have a greater sensitivity than passive tags, but they also last longer than active tags due to their ability of being able to produce an extensive power supply. Although semi-passive tags are suitable for numerous applications, such as animal tracking, access controlling and container tracking, the financial cost of this type of tags is higher than passive tags.

RFID Reader

The RFID reader is an electronic device which includes two basic parts: an antenna and a transceiver (See Figure 2.3). The antennas are designed to allow the open communication between the tag and the transceiver whilst the transceiver is responsible for acquiring the RFID data (Nagi et al., 2006). What is more, is that the RFID reader has a function of reading data from and writing data to RFID tag, which can be configured either as a hand-held, fixed-mount or hybrid devices. However, to ensure the compatibility of the communication, the tag and reader must work at the same specified working frequency and comply with specific regulation and protocols (Domdouzis et al., 2006).

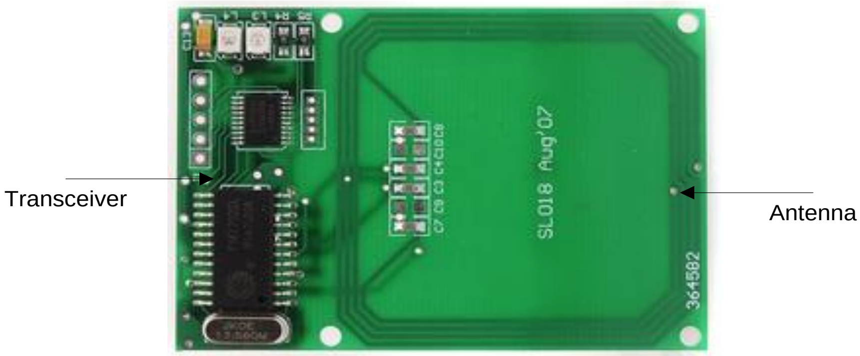


Figure 2.3: RFID Reader Structure (Strong Link, 2008)

2.1.3 Frequency range of RFID systems

Generally speaking, RFID frequency range is chosen according to the application area. Different frequency ranges of RFID tags result in various usages of RFID system in industries. The RFID frequency range is divided into three categories, which are Low Frequency (LF), High Frequency (HF), and Ultra-High Frequency (UHF). The range of LF is defined from 12 kHz to134 kHz, which is usually used in the application of Point of sales or livestock tracking. The HF range of RFID system is 13.56 MHz, which is applied in the security or access control area. There are two ranges in UHF which are 433-956 MHz and 2.45 GHz. The major use of RFID system in this range is related to the area of logistic service and object tracking. Nonetheless, the use of radio frequency spectrum is under the supervision by the government in every country. The RFID frequency operating range and feature is shown in Table 2.1.

Band	**Low Frequency (LF)**	**High Frequency (HF)**	**Ultra-high Frequency (UHF)**	**Microwave**
Frequency	30–300kHz	3–30MHz	300 MHz–3GHz	2–30 GHz
Typical RFID Frequencies	125–134 kHz	13.56 MHz	433 MHz or 865 – 956MHz 2.45 GHz	2.45 GHz
Approximate read range	less than 0.5 metre	Up to 1.5 metres	433 MHz = up to 100 metres 865-956 MHz = 0.5 to 5 metres	Up to 10m
Typical data transfer rate	less than 1 kilobit per second (Kbit/s)	Approximately 25 Kbit/s	433–956 = 30 Kbit/s 2.45 =100 Kbit/s	Up to 100 Kbit/s
Characteristics	Short-range, low data transfer rate, penetrates water but not metal.	Higher ranges, reasonable data rate (similar to GSM phone), penetrates water but not metal.	Long ranges, high data transfer rate, concurrent read of <100 items, cannot penetrate water or metals	Long range, high data transfer rate, cannot penetrate water or metal
Typical Use	Animal ID Car immobiliser	Smart Labels Contact-less travel cards Access & Security	Specialist animal tracking Logistics	Moving vehicle toll

Table 2.1: RFID Operating Frequency and Features (Ward et al., 2006)

Although standardization efforts through the International Organization for Standardization (ISO) and American National Standard Institute (ANSI) are assisting in compatibility, the legislation of frequency allocations may fluctuate from Europe to America. For example, the UHF range is defined as 868 MHz in Europe whereas it is 915 MHz in USA. The European standard of using UHF RFID was established by European Conference of Postal and Telecommunications Administrations (CEPT) in 2004. In addition, RFID equipments which operate under the standard UHF range would be able to work without license under the Wireless Telegraph Act 1949 Subject only to regulations intended to minimize the potential interference in Europe (Dobson & Todd, 2006). The frequency range defined by different countries is presented in Table 2.2.

Frequency	**Countries**
125–134 kHz	USA, Canada, Japan, Europe
13.56 MHz	USA, Canada, Japan, Europe
433.05–434.79 MHz	In most of USA and Europe and Europe and under consideration in Japan
865–868 MHz	Europe
866–869 and 923–925 MHz	South Korea
902–928 MHz	USA
952–954 MHz	Japan (for passive tags after 2005)
2400–2500 and 5.725–5.875 GHz	USA, Canada, Japan, Europe

Table 2.2: Global Frequency Range (RFID Working Group, 2005)

2.1.4 RFID Standards

Technically, a standard is a means used for defining calibration or the controlled artefact. Making and establishing a consistent standard is often an essential process for any application. RFID standards have a significant impact on numerous industrial applications, such as payment systems, good tracking systems and supply chains (Bacheldor, 2007). The lack of standardization or harmonization is considered to have a negative influence on the growth of industry. Despite the fact that a number of projects have been launched over the past years on developing standards for various RFID frequency and applications, it is commonly said that there is no globally consistent standard existing in RFID industry.

However, major RFID vendors have offered several incompatible standards with proprietary systems. A few emerging standards are also adopted in some RFID applications. The existing and proposed RFID standards regulate the RFID system as the communication protocol between tags and readers, the way data is organized or formatted and ways to test whether the products meet the required standards or not (Roberts, 2006).

The ISO and similar organization have been working together to develop standards for RFID applications, such as animal tracking with RFID. Moreover, ISO has created a standard for formatting the data structure on the tag (ISO 11784) and air interface protocol (ISO 11785). Payment systems and contactless smart cards adopt ISO 14443 and ISO 15693 for defining the air interface protocol used on RFID tags. Some other standards such as ISO 18047 and ISO 18046 have been established to test the conformance and performance of RFID tags and readers (Ward, 2006).

2.2 RFID Applications

RFID technology has been successfully integrated in a number of scientific and technical fields due to advantages of not line-of-sight, multiple reads, high speed, robust and programmability (Raza et al., 2006 & Liard, 2004 & Practel 2004 & Song 2003 & Teltra, 2004).

- **Not line-of-sight:** This non-line-of-sight communication between tags and readers increases the range of RFID applications And allows communication to take place through some materials.

- **Multiple reads:** RFID is not simply used to identify one item. Conversely, the information from a number of tags can be read from a long sensing range at the same time.

- **High speed:** RFID does not only have a multiple read function, but also contains a high speed transaction even when the tags are being read at a long distance.

- **Robust:** As RFID tags don't need to be read visibly, they are able to be combined with some materials to allow their survival in a harsh environment such as a corrosive chemical environment or rough handling situation.

- **Programmability:** RFID devices can be reused according to certain operations. The read/write function ensures the information can be stored in the tag as a unique identification number or the result of an item which has been tested.

- **Easy maintenance:** RFID devices do not require high cost maintenance and can be used without human interaction.

In the recent years, RFID applications have been widely adopted by various industries such as medicine and engineering. In medicine, RFID tagging is used in blood transfusions and analysis. In the automotive industry, RFID technologies are used in the assembly of new cars. RFID tags can be attached to parts of the cars and used to track the cars during the assembly process (Strassner & Fleisch, 2003). RFID technology has also been applied in the supply chain of the aeronautics industry. For example, Boeing ships tagged crates which are loaded with aeronautical equipment (Swedberg, 2005). In the retail industry, RFID tags are used to identify and track products along the retail supply chain such as in the Auto-ID system (Albrecht, 2001). The major use of RFID technology can be represented by the applications of position location, object tracking and activity monitoring.

2.2.1 Position Location

The area of position location has been well investigated by many researchers and academic institutions. In general, triangulation, scene analysis, and proximity are the three techniques that can be utilized for automatic location sensing. Different approaches in position locating are presented by several detailed technologies. For instance, Global Positioning System (GPS) is most used preferential technology for location determination worldwide. However, GPS needs to use at least four satellites to find a location; which is difficult to use in built-up areas (Siadat & Selamat, 2008 & Jin et al., 2006). In particular, it does not function effectively in an indoor environment as there is a reflection and attenuation with walls and other factors (Ni et al., 2003). Besides, the capital cost including mobile unit and infrastructure element are seen as major constraints for people to use GPS equipment. For example, a basic individual GPS receiver costs around US $100 and requires extra cost to update the global location of new objects (Hightower & Borriello, 2001). Thus, other alternative technologies such as ultrasonic location, Wi-Fi and RFID were created to rise above disadvantages of using GPS for locating position in an in-door environment.

Ultrasonic Indoor Location System

The first prototype of ultrasonic location system is represented by Active Badges, which was combined with the infrared technology (Want et al., 1992). It was replaced by the Active Bat location system due to the better accuracy of sensing the indoor location. According to Harter et al. (1999), the Active Bat gave 95 percent of accuracy at locating artificial bats within 9cm of the measurement. Moreover, the accuracy was improved by the Cricket location support system, which was estimated to a range of 4×4square-feet within a room (Priyantha et al., 2000). However, ultrasonic application requires a number of sensors to be mounted on the ceiling and the scalability, ease of deployment, and cost are considered as the main constraints to its deployment.

Wi-Fi Indoor Location System

Wi-Fi is the an acronym for wireless networking technology based around the IEEE 802.11 standards, wireless local area network (WLAN) technology. It has varied applications in home networks, mobile phones and other electronic devices. The centralized Wi-Fi location system can be represented by two classic applications: RADAR and Place Lab. RADAR is a building wide tracking system which was developed by the Microsoft research group in 2000. A measurement was made at the base station to compute the signal strength and signal-to-noise ratio (SNR) generated by the wireless devices. However, the drawback of RADAR tracking system was obvious during the operation process. Firstly, it was dependant on the support from wireless networking. Secondly, RADAR was only capable for providing two dimension positions in a building as it was difficult to present a three dimension position in a multi-floored building (Bahl & Padmanabhan, 2000). Although the new prototype (Place Lab) was developed with the assistance of GSM mates and Bluetooth devices, it suffered the disadvantage of low-end dynamic accuracy (LaMarca, 2005). Despite the fact that Wi-Fi technology is available for indoor position location, the system needs the support from WLAN, which may not be adaptive in a dynamic environment.

RFID Indoor Location System

As mentioned above, either ultrasound or Wi-Fi indoor position location systems require high infrastructure components. The ultrasound location system needs a fixed ceiling sensor for locating the position while the Wi-Fi technology is supported by the local wireless network. Nevertheless, the accuracy of location sensing generated from these two technology systems, the cost of devices and ease of the deployment are two obvious barriers for implementing these two technologies. In this case, RFID technology seems more attractive and applied when sensing the indoor position as an alternative.

A typical prototype of RFID location sensing system (Location Identification Based on Dynamic Active RFID Calibration: LANDMARC) was developed by the researchers from Michigan State University and Hong Kong University of Science & Technology. The concept of this system was to use a number of active tags as the reference tags for the location calibration. These active tags were fixed in some places to be the reference points in the system. The main approach of LANDMARC was to find out the object location by comparing the signal strength between tracking tags and reference tags and the real position of reference tags. This approach saved the cost of using expensive RFID readers and provides the system to be easily adopted in the real practice. Due to reference tags were fixed, the accurate and reliable location of being detected tracking tags was able to be measured (Ni et al., 2003).

However, some disadvantages of LANDMARC system were also obvious. Firstly, reference tags were compared with the tracking tags. The unnecessary computation was considered to be a major issue in this approach. Secondly, the real object position was computed by neighbouring reference tags and their weighting values, the error range of the locating result can be constrained in a polygon composed of neighbouring reference tags. Therefore, a proposed mechanism was introduced to improve the accuracy of LANDMARC by adding a triangulation mechanism to get the coordinate (x, y) of the target tag. This proposed mechanism reduced computing load by cutting down the number of candidates for neighbouring tags (Jin et al., 2006). Although the accuracy of this proposed mechanism was updated by Shih et al. (2006) as utilizing both reference tags and the mathematic algorithms, RFID position location system seems accurate only to a range of several meters (Casas et al., 2007). Regardless of the accuracy, the main purpose of using RFID location system is to provide a topological map rather than a topographic map because it is more useful to provide a layout of significant location in a complex indoor environment (Parry et al., 2007). This could be useful for route planning and progress monitoring.

2.2.2 Object Tracking

Many industries have applied RFID technology in their business process due to the low cost and simple infrastructure of the RFID application. However, the major application of RFID in object tracking domain goes through supply chains management, warehouse management, check-in and check-out system, construction material control and medical equipment allocation.

In supply chain management, RFID are used to track products from supplier delivery to warehouse stock and point of sale. It is considered to be the next generation application for replacing the barcode system which is currently and widely used in tracking objects from checkout through customer billing. In the RFID system, complete information about a product can be stored in the database. Manufacturers or retailers are able to query the location and delivery information. Moreover, RFID system is able to be used for ensuring safety in the supply chain. An example was shown in the US Food and Drug Administration (FDA) proposal. Particularly, FDA suggested each prescription drug should carry a read-only unique serial number so that the authenticity of those drugs would be guaranteed. In this proposed system, suppliers were able to track the tagged drugs during the shipping, and the purchasers could verify serial number when they bought drugs (HP, 2008).

Zhang et al. (2007) proposed a RFID material tracking information system (MTIS) to improve the automation within manufacturing enterprises. In MTIS approach, RFID tags, RFID middleware server, web server, database server and several readers including fixed readers, portable readers were adopted to construct six subsystems. In order to track the object, tags were attached with tracking objects. The basic information of objects was stored in the tags as well as the back-end database. The fixed reader transferred the information gained from tagged objects to the back-end database via the RFID middleware server. MTIS identified the moving object by verifying their information stored in the back-end database. A pass message would be given by MTIS if all the packages on the container had the same batch number.

The RFID material tacking application can be expanded in the construction industry. The successful examples of using RFID technology in the construction industry are carried out by automated tracking of pipe spools and tracking structural items on the construction site. For the pipe spools tracking application, RFID readers were located in the flatbed trailer while tags were attached with the pipe spools. Trailers carried the pipe spools to drive under the portal structure. This test showed the RFID could be effectively used in the construction environment (Song et al., 2005). While part of the scenario of tracking items on the construction site, RFID tags were allocated on a construction site for asset tracking. In this application, the engineer would be aware of the item which has been taken away from the site by the information stored in the tagged items.

Furthermore, using RFID object tracking system enhances the efficiency and effectiveness of managing moving objects. Significantly in the check-in and check-out system, RFID application benefits the improvement of daily procedure. As stated by Pala and Inanc (2007), RFID system improved the efficiency of the vehicle check-in and check-out procedure. It allowed several vehicles to check-in and check-out at the same time. In their research, a central database system was introduced to control vehicle parking status. With this RFID vehicle tracking system, all the parking-lots in a city could be operated in an economical approach. Similarly in the RFID library check-in and check-out system, RFID is able to help library systems track physical location of a man or tagged books. As RFID readers were set within the building, it is rather possible for library system to map the location of these RFID readers and client platforms (Chen et al., 2007).

2.2.3 Activity Monitoring

The most common method for activity monitoring is to employ the video equipment. However, using video facilities for activity sensing is constrained by the four obvious limitations. Firstly, the price of digital camera is expensive. The financial concerns are always a trend inflicting a barrier to any organization or individual user. Secondly, the camera has to be re-deployed if there are changes from the tracked trajectories. Thirdly, one camera can only monitor the certain trajectories. It is difficult to monitor the other region at the same time. Finally, it is hard to detect any irregular activities. The captured image from multiple cameras can not be easily automatically analysed (Liu et al., 2007).

Since the financial concerns and other limitations of using video monitoring, the alternative technology (RFID) has been introduced by many researchers for detecting the personal activity. As RFID tags can be easily attached with moving objects, it is possible for RFID system to record the individual movement and the information which is associated with them. One example of RFID activity monitoring is presented in the hospital environment. Some hospitals use RFID system to monitor the new born baby, which prevents any kidnapping and sound an alert to the hospital staff if unauthorised people take the baby outside the hospital. For instance, in the recent application undertaken at Lucile Packard Children's hospital in USA, newborns were attached with RFID tags in order to ensure the security of their movement. Some medical centres adopted RFID in indentifying the patients' medical needs (Anshel & Levitan, 2007). Given that the flexible capability of the RFID tag can be allocated into the highly mobile objects, the application of activity monitoring has been concerned to be of practice in other industries. For example, one large casino in Las Vegas planned to implement passive RFID tags in each gaming clip, and place the RFID readers at the gaming table and cashier stations. This approach ensured the possible surveillance of both clips' movement and players' activities (Weinstein, 2005).

The idea of using object's movement to infer a person's activity was supported by Philipose et al. (2004), who conducted a research of using RFID paradigm to infer activities from interaction with objects. Activity inference needs to define how many steps are involved when undertaking one activity and how the data is detected from tagged objects, to signify activity. For example, having a cup of tea can be seen as a 3-stage activity: boil the water, brew the tea in the water and then give flavour to the tea. In their research, every single activity was connected to several involved tagged objects. The lightweight natural-language-processing techniques were used to transfer each step into a stage in their activity model. Once the involved objects were specified, the object involvement probabilities were defined, which intuitively describes the probability of using the object in the activity stage. Likewise, Krahnstoever et al. (2005) presented a prototype system of using both video camera and RFID to detect people's motion. The purpose of adopting RFID was to predict the human motion by analysing the RFID tags' presence, movements and orientation in 3D spaces. Hence, the movement of object was detected by the orientation changes and filed strength of the attached RFID tags. For inferring the certain actives, a person reaching or grabbing an object could be easily observed by the camera; however, it was hard to estimate what this person is doing with the object. By observing the subsequent relevant movements, it was possible to detect what the person was doing with the item. If the person retracted his hand and the object leaves the emitter field, it could be inferred that the person was holding the object in his hands.

At the same time, Fishkin et al. (2004) created two RFID based prototypes for human activity monitoring; which are iGlove and iBracelet. iGlove was firstly designed as a bike glove and then used as a medical glove in the hospital. iGlove consisted of a RFID sensor for reading tags, a remote radio which wirelessly transferred sensory information to a PC station, and a rechargeable battery for the power supply. The principle of using iGlove followed the concept of inferring personal action from RFID tagged objects. By tracking the object recorded using the glove; it was possible to determine the time and activity performed by the person. Unfortunately, iGlove was only accepted in a small population due to the limitation that it was compromised by the diffusing sweat from hands of the bearer. Therefore, another prototype iBracelet was made to replace the iGlove. iBracelet comprised RFID reader, power board, battery, tensioner and antenna. Although iBracelet had better aesthetical and ergonomical design and accepted by larger population than iGlove, both of them were developed from the RFID reader. In contrast, Smith et al. (2005) presented another prototype (the Wireless Identification and Sensing Platform) by using the long range passive tag to detect object motion. The Wireless Identification and Sensing Platform (WISP) was integrated with sensors and activated by the RFID reader, which contained similar capabilities to the active beacons of delivering the motion detection. The initial type α-WISP consisted of one antenna and two mercury switches. It utilized two clips ID to indicate the physical object. However, α-WISP was suffered by the drawback of lacking of sensitivity in two of the three spatial directions. Therefore, the three-axis sensor π-WISP was created to overcome this disadvantage. The new prototype required a more complex hardware platform than the α-WISP, which had a power-harvesting circuit, a microcontroller, an accelerometer and a multiplexer. For inferring the activity, objects were attached with the system in order to track their movements. If a tagged object was used, the reader would be notified by triggering the accelerometer. As a result, the activity was able to be detected.

2.2.4 Activity Monitoring of Using RFID Sequence

The previous researches indicated that RFID application in human activity monitoring was based on the interaction with objects. As RFID tags are easily attached with objects, certain human activity can be represented by a series of tagged object ID. According to Philipose (2005), the inference system requires a model for converting from observed objects to the activity label. Thus, the main purpose of using RFID system for activity inference is to analyse the information of interacted objects with certain individual motions. Although there are a number of approaches that are available for activity monitoring, the simplest way is to estimate the movement of the user in relation to landmarks or tagged items (Parry et al., 2007). In other words, the RFID activity monitoring is related to suggest human activity by exploring a group of sequence generated from the RFID system.

One example of using RFID data stream for detecting human activity was shown in the research conducted by Liao and Lin (2007), which deployed a RFID model to estimate the shopping path and the products purchased by the customer in a supermarket environment. In particular, active RFID tags were used and attached with shopping carts. RFID readers were fixed along the entrances, exits and aisles of the floor in the supermarket. When a shopping cart entered the monitoring area, the cart's ID and the time of passing were recorded by the reader and then transferred to database by the gateway servers. When a customer got to check-out point, the shopping cart ID and purchased goods were recorded in the database as well. Therefore, the raw RFID data generated by the system in the database was a group of sequences which contained the cart ID, time and location. Several algorithms such as Customer Access Matrix (CAM) and Customer Transaction Mining (CTM) were applied in deciphering the raw sequence in order to find out the preference segment of the shopping path and the relationship between shopping path and purchase items of the customer. The experimental result in this research showed it was possible to adopt the proposed model to detect human activity in the supermarket environment.

2.3 Summary

The development of RFID technology has gone on for several decades. A typical RFID infrastructure consists of reader, tags and host system. With the advantages of lower cost and less infrastructure than GPS and Ultra sonic technologies, RFID has been applied in object tracking, position location, and indoor activity monitoring. In position location scenario, the main concept of using RFID position location is to provide a topological map rather than a topographic map. The major deployment of RFID technology in object tracking is conducted in the supply chain where a significant improvement of operating check in and check out system has been carried out. Besides, utilizing RFID tagged objects for activity monitoring has been presented by several researchers. The individual motion can be inferred by tagged objects which the person interacted with. Furthermore, the RFID data sequence has been proposed in monitoring some certain movements as well. However, applying appropriate mathematical algorithm for filtering raw RFID data stream would be useful for improving the accuracy of activity inference.

Chapter 3

Research Methodology

The aim of this research is to examine personal activity by using RFID detection records in an assisted living context. This particular activity detection is a based on human interaction using the RFID tagged object. It is hoped that the activity undertaken by the person can be determined by recording the detected tags sequence. Philipose et al. (2004) presented that personal activity inference referring to the human interaction with tagged object needs to define every single process involved in one certain motion. Each activity performed by the group of people involved can be seen as interactive actions towards the relevant object. The information detected from these tagged objects indicates the specific activity which has been executed by the people (See Figure 3.1).

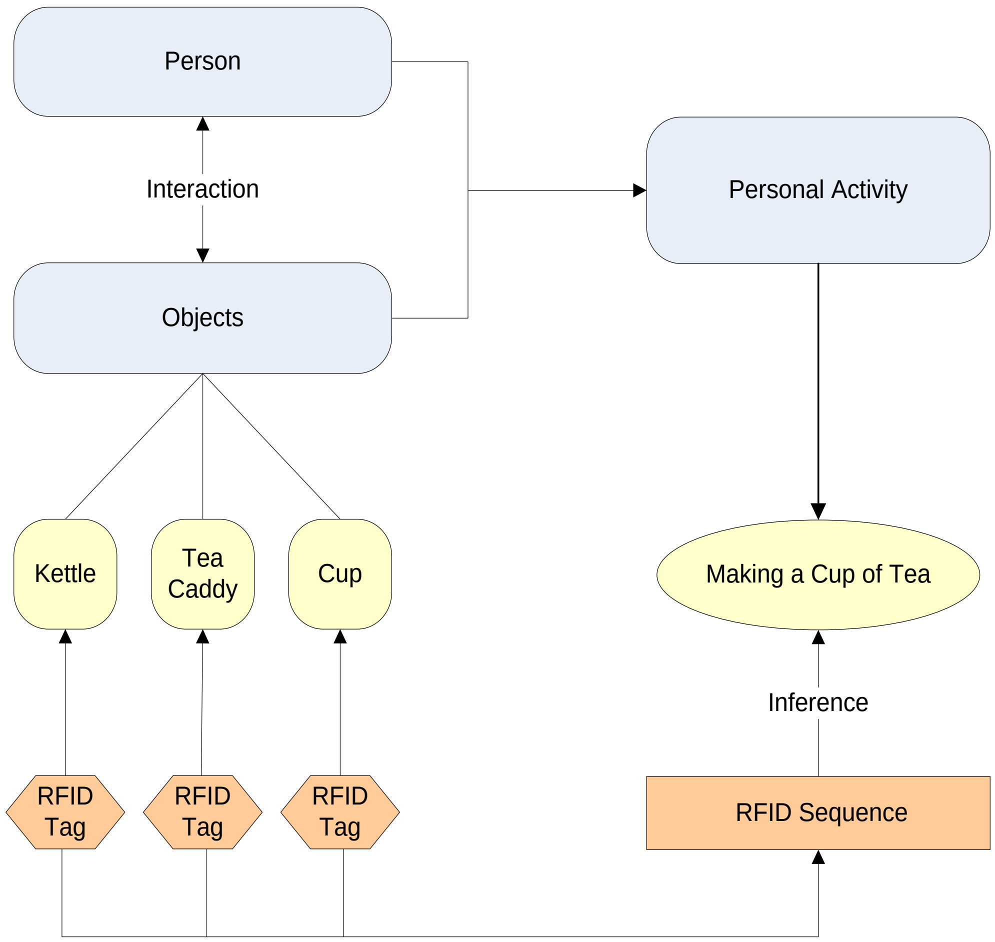


Figure 3.1: The Scenario of Personal Activity Inferred by RFID Sequence

This idea has motivated some researchers to develop RFID devices for inferring personal activity in the experimental environment. Krahnstoever et al. (2005) used RFID devices for the assistance of human activity detection. Fishkin et al. (2004) designed iGlove and iBraclet, which were two RFID devices applied in the medical profession for monitoring the hospital staff's activity. Moreover, Smith et al. (2005) expanded the usage of RFID tag for creating a prototype WISP which can be used in human activity detection. In these experiments, the RFID reader was carried by the person and the tags were located on objects and landmarks. Therefore, the RFID data generated from RFID system has a significant relationship with an individual's activity. The unexpected interferences appeared between RFID equipments may result in the misapprehension of information to users. Previous research shows that false readings occurred during the time when RFID reader detects the RFID tags. These false readings led to problems in object tracking such as flickering on the graphical user interface of the smart medicine cabinet and incorrect operation within the process of stack control (Floerkemeier et al., 2003; Mc-Falane, 2002 & Brusey et al., 2003). In

RFID activity monitoring scenario, the activity analysis is based on the relevant RFID data stream. False readings may generate data stream including the unnecessary object's ID involved in some certain activities. Thus, the reliability of using RFID data stream for activity monitoring is an area of concern for many researchers. Due to the interest in exploring this type of issue, the main research question in this objective has been proposed as follows:

Can RFID detection sequences be used to infer activity? More specially, how can the data stream be cleaned to support activity detection?

To investigate the research question, a quantitative approach using the design science study has been adopted to examine RFID sequence usage for predicting the human activity. Design science is the information technology research methodology, which offers a paradigm for problem-solving within the research projects. Lee (2000) indicated that the design science paradigm plays an important role in dealing with problems appearing in the information technology researches. It is sometimes seen as "*improvement research*" which accelerates the improvement of activity performance (Jarvinen, 2005). A design science study seeks a creative way to effectively and efficiently accomplish the analysis, design, implementation and the use of information system (Denning, 1997). The main focus of design science is to find the effective approach rather than examine whether it is true or false to use a certain method. This is proactive with technology which is involved in the innovated technological artefacts that has presented an impact on people and organizations. *"It often takes a simplistic view of the people and the organizational contexts in which designed artefacts must function" (*Hevner et al., 2004*)*. The general stage of design research methodology is shown in Figure 3.2, which contains several stages such as awareness of problems, suggestion, development, evaluation, and conclusion (Vaishnavi & Kuechler, 2004).

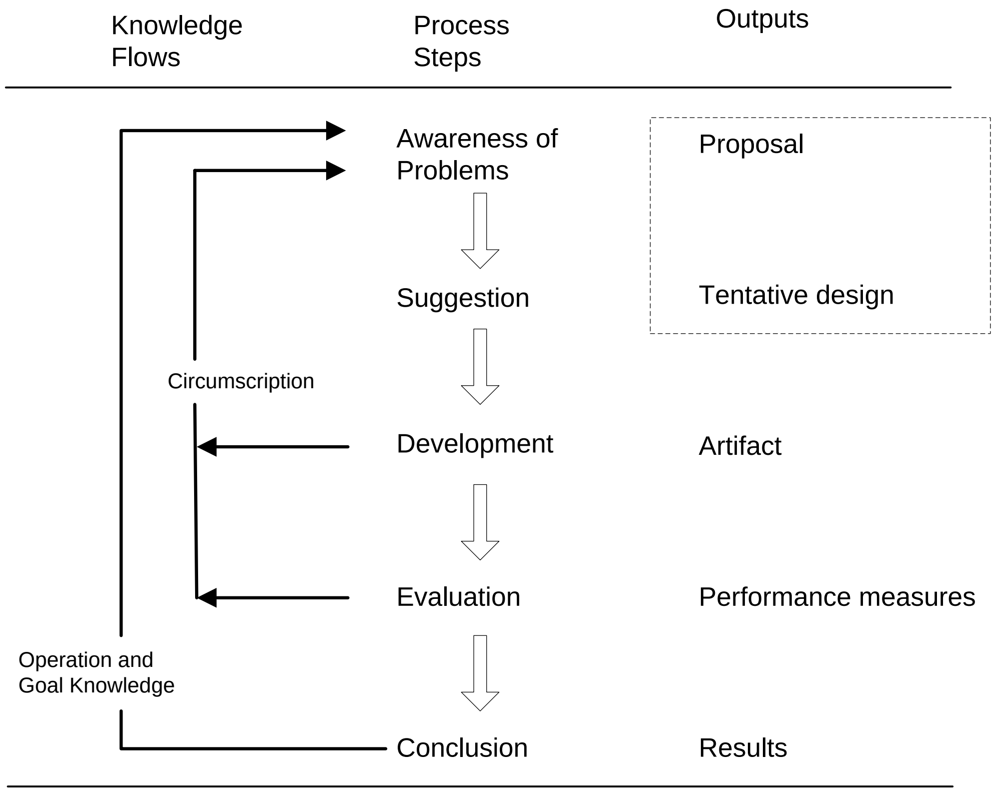


Figure 3.2: Design Science Methodology (Vaishnavi and Kuechler, 2004)

According to the procedure of design science methodology, a possible resolution is required to carry out after the awareness of the research problem. Experimental analysis is a common approach for the researcher to highlight and solve issues in the scientific project. There are two general approaches that are frequently used in RFID research project, which are simulation and real experiment. Simulation method focuses on providing a model for finding and solving problems by utilizing a computer programme in the virtual environment (Balci, 1995). Simulation is mostly adopted to evaluate the performance of RFID reader rate or algorithms for determining the location in RFID researches (Breaha & Jons, 2006 & Rubin, 2005). However, the data generated from real experiment is more accurate than that in the simulation circumstance. Using real experiment enables the user to gather and analyse the data in the real and specific situation, which also guarantees the reliability of the test and experiment result (Dziadak et al., 2006). Most researchers use real experiment methods to investigate the RFID application in object tracking and activity monitoring (Fishkin et al., 2004 & Song et al., 2005). Hence, the real experiment will be conducted to obtain and resolve problems for this research. The experimental design is shown in Figure 3.3.

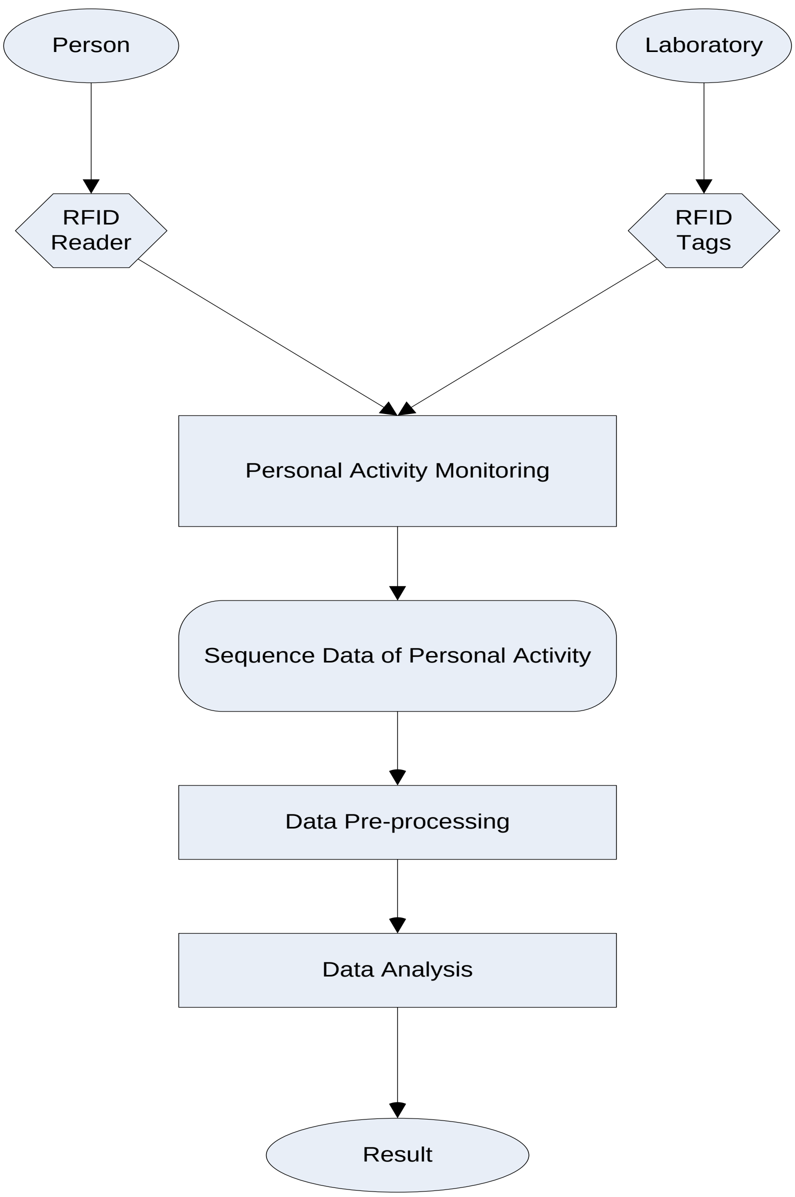


Figure 3.3: Experimental Design

In this proposed experiment, a number of RFID tags will be located around the laboratory and placed on different objects and the user will be equipped with a tagged RFID reading device. When the user passes the tags, the RFID reader is able to detect and record the tag ID. After each activity, the reader will be connected to the workstation to extract RFID data. As tagged object's ID is considered as the essential information used for inferring the personal activity in this research, the habitual activity undertaken by the people can be represented by a series of RFID data sequence. Taking the example of having a cup of tea in this scenario, given that the landmarks are several objects located in different places in a room such as ABCDE, each person is required to pass through these landmarks A, C, B, D, E respectively to complete this habitual activity (See Figure 3.4). The personal motion of making a cup of tea shown in a RFID dataset can be seen as a sequence of ABCDE. Likewise, the other activity is able to be represented by different RFID sequences such BACED or ADECB. However, the main challenge of using RFID data stream for inferring personal action is to determine and clean the erroneous data produced by false readings. Thus, using an appropriate method to deal with the false reading is an essential step in this experiment. The data pro-processing stage is designed to solve this problem. All sequence generated from RFID system will be pre-processed at the end of data collection. The pre-processed dataset will then be analysed in order to compare the standard RFID sequence which is assigned to signify personal activity in this research. Finally, the result will be analysed out to assess the hypothesis as mentioned above.

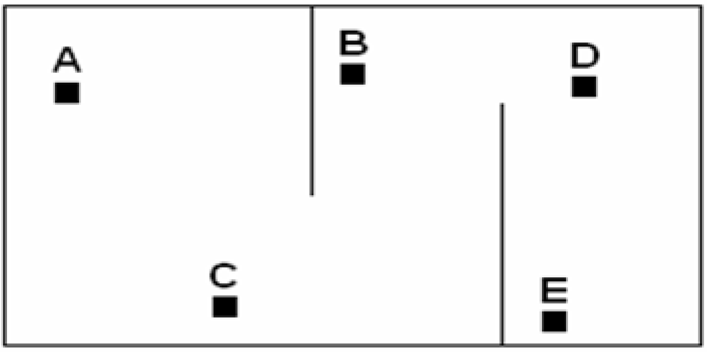


Figure 3.4: Diagram of locations for the Human Activity Detection scenarios

Chapter 4

Experimental Design

The construction of the experiment in this research focuses on investigating the main research question of whether RFID sequence can be used for inferring personal activity. The principle of using RFID devices to monitor human motion in an indoor environment is to estimate the personal interaction with the tagged objects or landmarks. To present activity tracing, researchers usually conduct the experiment by placing RFID tags in/on the objects or in the different locations of a room. Consequently, a RFID system comprising tags and readers needs to be set up in order to perform the experiment.

4.1 Experiment Setup

The RFID system used in this experiment consists of several RFID tags, one RFID reader, one workstation and the specific software for extracting the RFID dataset from the RFID reader. The following part describes the used RFID tag, RFID reader, workstation and software in this experiment.

4.1.1 RFID Tag

The category of RFID tags adopted in previous experiments by the researcher for detecting human activity can be either passive or active. Although active RFID tags are able to emit the radio frequency signal, the drawback of using active tags is also obvious such that they usually have a big size and need independent power supply to support the radio frequency emission. On the other hand, the financial concern always seems to be a bigger barrier for researchers to obtain some certain devices. In the event of using RFID equipments for demonstrating personal activity monitoring, RFID tags are one of the essential components for constructing the RFID system. In this experiment, tags are required to be put in different areas or allocated in several objects in an indoor environment. This means there are not only one or two tags that are needed to be purchased. Due to the fact that only the RFID tag ID is used to represent the landmark of a room or some specific objects, it is unnecessary to use larger and more complex active tags. Hence, cheaper and smaller passive RFID tags are capable enough for performing the experiment. Moreover, Ultra High Frequency (UHF) passive RFID tags are applied in this experiment because it has longer detecting distance than the other types of passive tags. Considering and comparing the various UHF passive RFID tags in the market, the Alien World Tags (ALN-9540 - "Squiggle™") was chosen to construct the RFID system (See Figure 4.1). The ALN-9540 - "Squiggle™" UHF passive tags has global operation range from 860 to 960 MHz and designed in the size of 97mm x 11mm, which enable each individual tag to be used successfully across the Americas, Europe, Asia and Africa and their unique RFID operating frequencies (Alien, 2008). The key features of used Alien passive UHF RFID tags are shown in Table 4.1.

Figure 4.1: Alien UHF RFID Tag-ALN-9540 - "Squiggle™"

EPC Class 1 Gen 2 / ISO 18000-6C
Exceptional range
High-speed programming for seamless manufacturing integration
World Tag operates at global frequencies 860-960 MHz
Available in high-yield, high-capacity rolls for high volume converting processes
Alien Higgs™-2 IC

Table 4.1: Key Features of Alien ALN-9540 - "Squiggle™"

4.1.2 RFID Reader

The RFID Reader has been used in the different approaches for monitoring personal activity in the previous literatures. Some researchers utilized the RFID reader as a fixed sensor which was located on the ceiling to receive the signal transmitting from RFID tags. Mostly, the other researchers preferred assigning the RFID reader to the person rather than fixing it at certain locations to capture the RFID tags' signal. In these experiments, RFID tags were allocated in some areas or some objects and the person was equipped with the RFID reader. This is complementary to our experiment where a person needs to take the RFID reader and have some activities identified by passing tagged objects in an indoor environment. Therefore, the RFID reader must be compatible with the chosen tags and easy to handle during the experiment. In other words, the reader should not be too heavy or too big for a person to carry and should be able to detect the UHF RFID passive tag. As the RFID reader produced by Alien seems only suitable to be implemented in big organizational environments, another UHF RFID reader - Tracient Padl-R UF was employed for performing an individual indoor activity monitoring (See Figure 4.2). The Padl-R UF RFID reader is designed in the size of 210mm (h) x 70mm (w) x 15 mm (d) with the frequency range from 855 to 960 MHz. It has a lightweight feature (135 grams) that contains both USB and Bluetooth connectivity, which can be used in stand alone (data logging) mode or wirelessly to connect to a handheld electronic devices such as PDA, desktop or laptop. Additionally, it is capable for operating with ISO 1800-6b or c tags (EPC GEN2) (Tracient, 2008). The main features of Trancient Padl-R UF RFID reader are presented in Table 4.2.

Figure 4.2: Tracient UHF RFID Reader- Padl-R UF

Size	210mm (h) x 70mm (w) x 15 mm (d) (approx)
Weight	135 grams (approx)
Operating temperature/Storage temperature	-10 to +60º C
Ingress Protection	IEC 529 IP64
Approvals	CE, C-Tick, FCC, EN302 208, EN301 489, EN 60950
Drop Specification	1m to plywood on concrete, all faces and corners.
User Interface	Single button for RFID reading, Multi-colour Leds, Audio beeper (multi tone). Configurable use case scenarios via USB or Bluetooth.
UHF Transponder	ISO 18000-6A, ISO 18000-6B, ISO 18000-6C, EPC Class 0, EPC Class 1 (GEN2), and UHF Proprietary
Approximate read range	1.5m (typically, depends on transponder)
Date rate	~40kbps (EPC C1G2), ~80kbps (ISO 18000-6C)
O/P Power	0.5W
Bluetooth Interface	Class 2 (typically 10m operation).
Antenna	Internal only
Additional Data Communication Interface	USB-mini-B connector for wired applications
Power Supply	Via USB for high-capacity internal Li-Ion battery recharge
Firmware Support	Field upgradeable via USB. Some configuration settings also available via Bluetooth interface.

Table 4.2: Main Features of Tracient Padl-R UF RFID reader

4.1.3 Workstation:

The purpose of conducting this experiment is to infer the individual activity by analysing the RFID data stream. Due to personal activity that can be seen as an interaction with the tagged objects, the information about which objects the person interacted with is the only source for inferring some specific activities. Therefore, generating RFID data stream from the RFID Reader is a crucial step in this experiment. As Tracient Padl-R UF RFID reader provides USB and Bluetooth connectivity, it is able to extract the RFID data detected by the RFID reader to either a PDA, desktop or laptop. In this experiment, one desktop was implemented as the workstation for the RFID system. The general features of this workstation are shown in Table 4.3.

Desktop Producer	Cyclone PC
CPU	Inter(R) Core(TM)2 6300
Memory RAM	2G
Hard Disk	160G

Table 4.3: General Features of Workstation

4.1.4 Software

Any hardware needs adequate support from the specifically designed software in order to work, where software ensures the workability of the hardware. In this experiment, the software was installed in the workstation and used for configuring RFID reader and extracting RFID data stream from the RFID reader. Thus, the Tracient Software Development Kit (SDK) was installed in the workstation for the RFID reader configuration and RFID data sequence extract. Performing the reader configuration, Tracient SDK offers the RFID Control Panel for both PDA and PC (See Figure 4.3). While taking log download from the Tracient RFID reader, RFIDSync was used to carry out this function (See Figure 4.4). The log download can be saved into various formats such as MS Excel or plain text, depending on the requirement from the user.

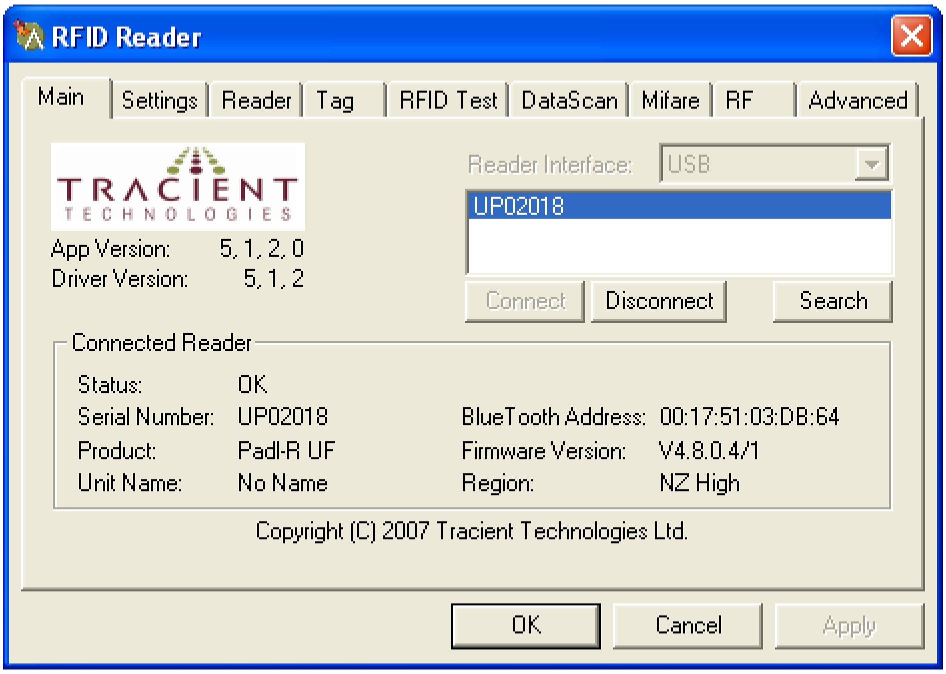


Figure 4.3: Tracient RFID Control Panel

Figure 4.4: Tracient RFIDSync

4.2 Experimental Procedure

As mentioned earlier, the information regarding the objects that were allocated with RFID tags plays a critical role of inferring personal activity in this experiment. By detecting RFID dataset recorded in RFID data reader, the activity undertaken by the person is expected to be determined. To conduct the experiment, several RFID tags were set in some locations of laboratory or in/on some objects in the laboratory. In the RFID reader configuration step, the read mode was set in a continuous status, the read interval was set to 0.20 second. So, in this case, the reader was able to record tag detection five times per second. At the same time, the reader was configured to record tag ID as well as logging the time when the tag ID was detected (See Figure 4.5).

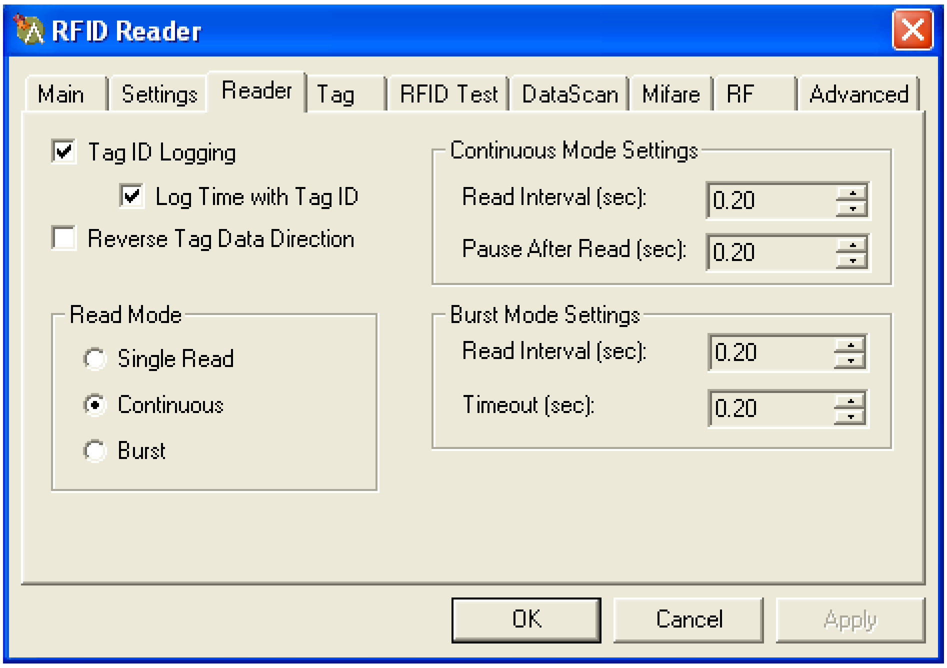


Figure 4.5: Tracient Padl-R UF Reader configuration

For performing the personal activity monitoring, the user was required to carry a RFID reader during the entire experiment process. When the user passed the tagged place or object, the RFID reader could receive signal reflecting from RFID tags. As a consequence, the information of these RFID tags was recorded by the RFID reader. RFID reader was connected with the workstation via USB port at the completion of one activity. The raw RFID dataset was extracted from the RFID reader and saved into certain format such as MS Excel or plain text. The main procedures of this experiment are concluded as follows:

- Configure the RFID reader
- Place the RFID tags in/on targeted objects or in different areas of a laboratory
- Define the start and end points of the activity which the user intends to take
- Equip the RFID reader to the person and switch on the RFID reader
- Demonstrate the specific personal activity as user interacted with the tagged objects by taking an equipped RFID reader in the laboratory
- Switch off the RIFD reader and connect it to the workstation
- Extract the information of detected RFID tags from the RFID reader and save it into required format.

4.3 Experiment 1

The personal activity undertaken in an indoor environment can be seen as either linear movement or nonlinear movement. The initial experiment emphasized the detection of linear movement. To perform this experiment, one table (length: 1.2m approx) was utilized to be a platform for processing personal activity on a linear way. By following the experiment procedures, the reading frequency of RFID reader was configured as five times per second. Four examples of UHF RFID passive RFID tags were chosen and put in a line with the same space on one side of the table. The distance between each tag was measured as approximately 0.4m. Because the default ID of these RFID tags was a long serial numbers such as E2003411B802011029356365 or E2003411B802011029356363, the simple and unique ID such as T6 or T5 were assigned to each tag in order to easily distinguish their positions on the table. Consequently, these four RFID tags were marked as T9, T6, T8, T5 and were put separately and orderly from each other. After labelling new tag ID, the user needed to determine the start and end points before starting the certain activity. In the linear movement, the tag T9 was defined as the start point whereas the tag T5 was seen as the end point. The user then carried a RFID reader to walk besides these four tags. This activity was set in five times loop, which means the user was required to walk in the same route by passing the RFID tags T9,T6,T8,T5 for five times. The RFID reader was switched off after passing the end point and then connected to the workstation to extract raw RFID sequence representing for each track. While the RFID reader was switched on again the user went back to the start point to begin the next track. The previous dataset stored by the RFID reader was erased before performing the next track. The scenario of linear movement is shown in Figure 4.6.

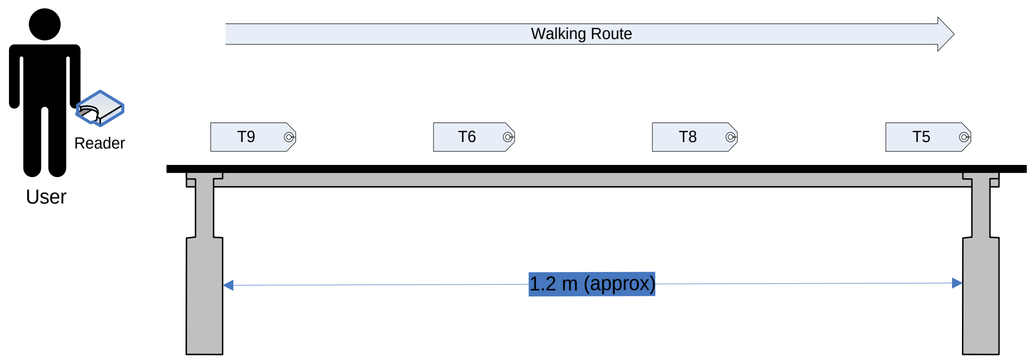


Figure 4.6: Linear Movement

4.3.1 Experiment 1 Result

The RFID reader was connected to the workstation to extract RFID dataset after every single track. Hence, there were five RFID datasets in total generated in this experiment. Each raw RFID dataset was downloaded from the RFID reader to workstation via RFIDSync. Moreover, the dataset was automatically formatted as plain text and stored in the workstation. In the five raw datasets that were examined, each log contained the RFID tag ID and the time when the reader detected these four tags. A sample of original RFID dataset generated by the Tracient RFIDSync is shown in Table 4.4. Five original RFID dataset of linear movement are shown in Appendix A.

Irrelevant Tag ID

Original Tag ID	Original Time Log	Assigned Tag ID
E2003411B802011029356356	00:23:52 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:23:53 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:23:53 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:23:55 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:24:01 09/Sep/2008 (GMT)	T6
E2003411B802011029356367	00:24:10 09/Sep/2008 (GMT)	T9
E2003411B802011029356367	00:24:10 09/Sep/2008 (GMT)	T9
E2003411B802011029356367	00:24:11 09/Sep/2008 (GMT)	T9
E2003411B802011029356367	00:24:12 09/Sep/2008 (GMT)	T9
E2003411B802011029356356	00:24:15 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:24:15 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:24:16 09/Sep/2008 (GMT)	T6
E2003411B802011029356356	00:24:17 09/Sep/2008 (GMT)	T6
E2003411B802011029356357	00:24:19 09/Sep/2008 (GMT)	T8
E2003411B802011029356357	00:24:20 09/Sep/2008 (GMT)	T8
E2003411B802011029356357	00:24:20 09/Sep/2008 (GMT)	T8
E2003411B802011029356357	00:24:21 09/Sep/2008 (GMT)	T8
E2003411B802011029356368	00:24:23 09/Sep/2008 (GMT)	T5
E2003411B802011029356368	00:24:24 09/Sep/2008 (GMT)	T5
E2003411B802011029356368	00:24:25 09/Sep/2008 (GMT)	T5

Table 4.4: The Sample of Original RFID Dataset of Linear Movement

Due to the limitation that only the primary RFID tag ID was stored in the reader, the assigned tag ID was used to replace the initial one via software. The start and end time-points of this activity was predefined, thus, if the irrelevant tag ID appeared, it is removed from the beginning or at the end of the original data stream (highlighted part in Table 4.4). Consequently, the RFID dataset that was used to represent the personal activity in this experiment began with start point and finished with end point. Besides, only the time and the tag ID were allocated for new datasets rather than adding minor details such as date, moth and year that were involved in the original data stream. Finally, the customized dataset of each track only contained two parameters: Time Log and Assigned Tag ID (See Table 4.5). The customized dataset of five tracks in linear movement experiment is shown in Appendix B.

Time Log	Assigned Tag ID
0:22:02	T9
0:22:03	T9
0:22:03	T9
0:22:04	T9
0:22:05	T9
0:22:05	T9
0:22:06	T6
0:22:06	T6
0:22:07	T6
0:22:08	T6
0:22:10	T8
0:22:10	T8
0:22:11	T8
0:22:12	T8
0:22:12	T8
0:22:15	T5
0:22:16	T8
0:22:16	T5
0:22:16	T5
0:22:17	T5

Table.4.5: The Sample of Customized Dataset of Linear Movement

Taking the tag ID from the dataset above and arraying them based on the relevant time series, the linear movement of these five tracks can be represented by the RFID tag sequence (See Table 4.6).

Track Number	Tag Sequence
1	{T9, T9, T9, T9, T9, T9, T6, T6, T6, T6, T8, T8, T8, T8, T8, T5, T8, T5, T5, T5}
2	{T9, T9, T9, T9, T6, T6, T6, T6, T8, T8, T8, T8, T5, T5, T5}
3	{T9, T9, T9, T9, T9, T6, T9, T9, T6, T6, T6, T6, T8, T8, T8, T5, T5}
4	{T9, T9, T9, T6, T9, T9, T6, T9, T6, T9, T6, T6, T6, T6, T6, T8, T8, T8, T5, T8, T8, T8, T8, T5, T5, T5}
5	{T9, T9, T9, T9, T9, T9, T6, T9, T6, T6, T6, T6, T6, T5, T8, T8, T8, T8, T5, T5, T5, T5}

Table 4.6: Tag Sequences of Linear Movement

The activity carried out by the user in this experiment is a linear movement. The user was required to walk in a predefined route, at a constant rate passing the RFID tags in the order: T9, T6, T8 and T5. Ideally and theoretically, the RFID dataset generated in this experiment should be an array such as: {T9, T6, T8, T5} or {T9…T9, T6…T6, T8…T8, T5…T5}. Note that the sequence here can be seen as an array which consists of four individual groups T9, T6, T8 and T5. Each group must contain the same value and be followed by the others in order. For instance, there is only tag ID T9 existing in the group of T9 rather than the other tag ID such as T6, T8 or T5. In this experiment, however, excepting the second track, the RFID sequence representing the rest of tracks seems unable to match the theoretical one. As there is a possibility that the RFID reader is able to detect several RFID tags at the same time, it is not surprised that different values emerged in one group of the RFID data sequence. The dataset of first, third, fourth and fifth tracks show that the RFID reader recorded the different tags at the same time. In order to have a clear view on the problem hidden in these RFID data stream, five datasets were plot out by defining the time log series as X axis and the location of these four RFID tags as Y axis (See the following charts).

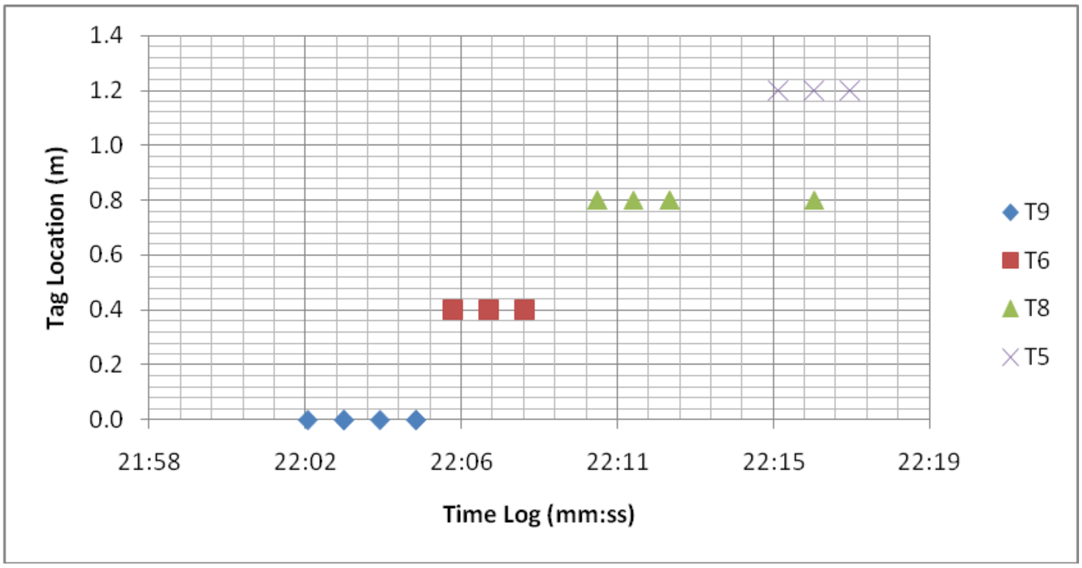


Figure 4.7: 1ST Track

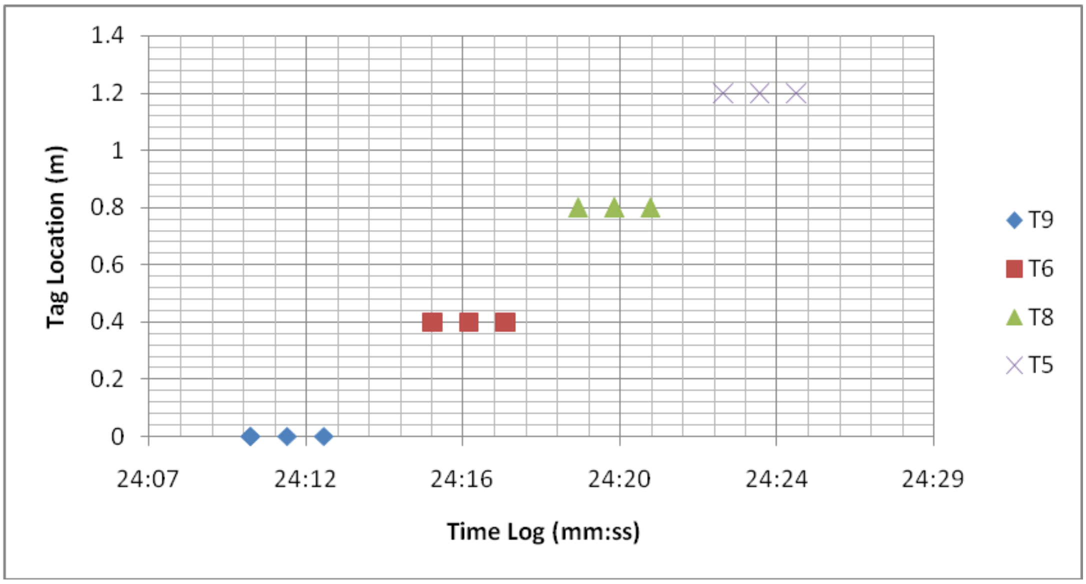


Figure 4.8: 2nd Track

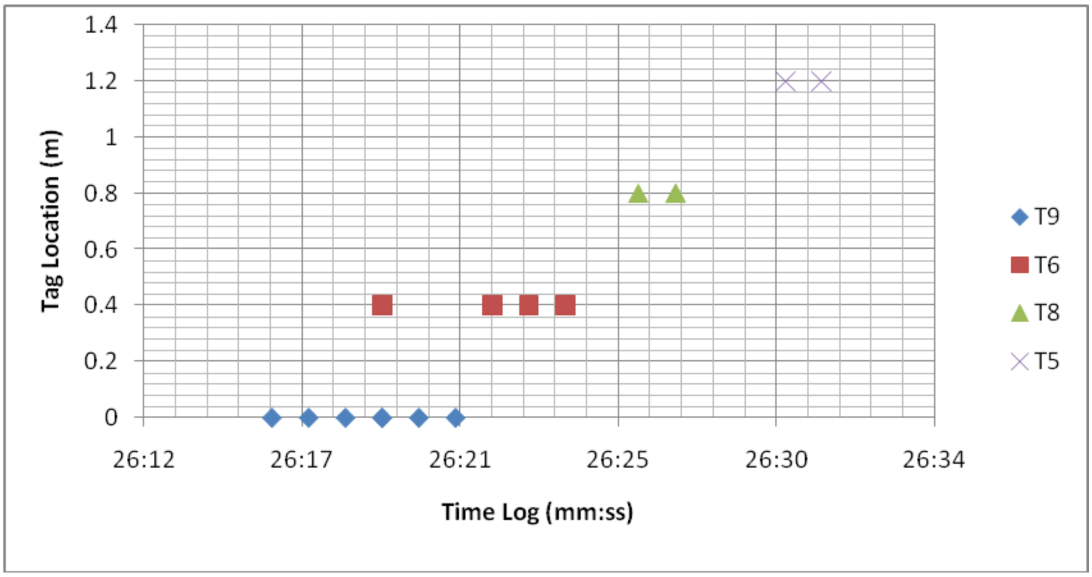


Figure 4.9: 3rd Track

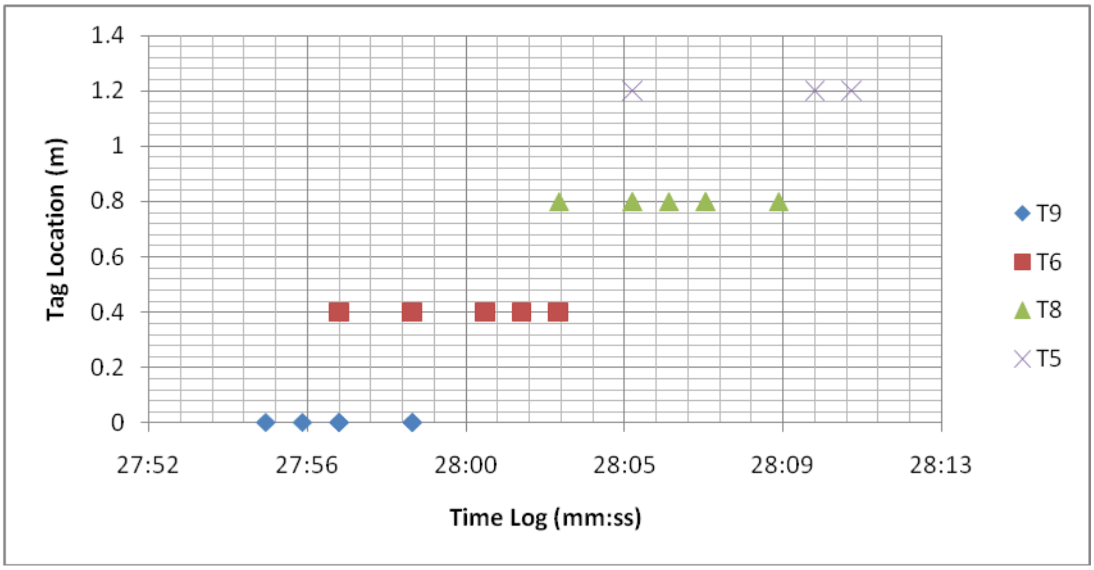


Figure 4.10: 4th Track

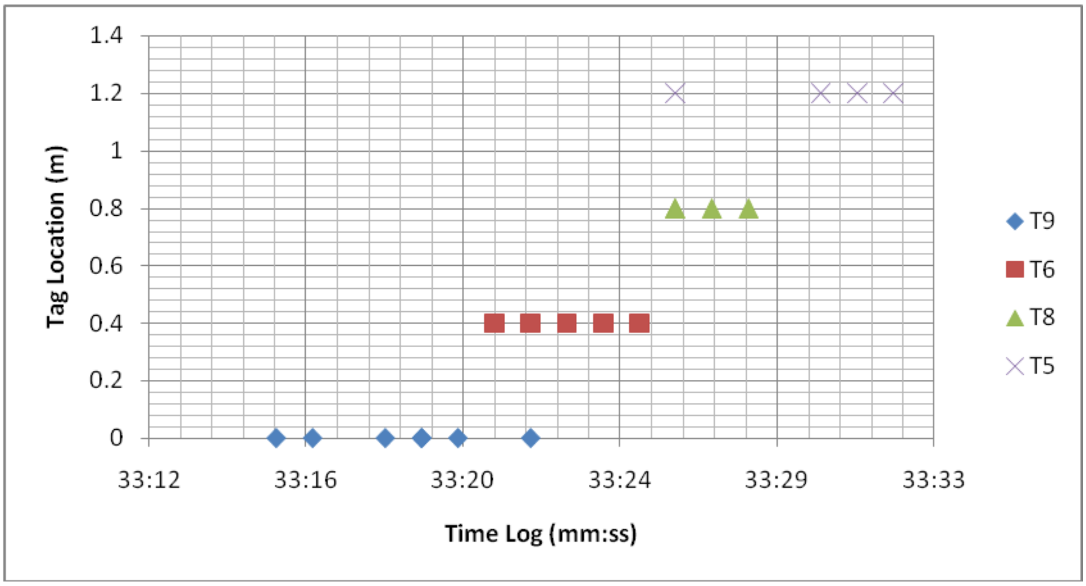


Figure 4.11: 5th Track

The RFID tags T9, T6, T8 and T5 are presented in different colours and shapes in five figures above. The diagram of 2nd track (Figure 4.8) illustrates that each group of tag was separately sensed by the reader at different time. There was no overlapping time appearing in four individual groups in the 2nd track. However, the other four figures indicate that some tags were read at the same time as they display in the same column. As observed from these four diagrams, there are two tags detected by the reader at each overlapping time during the linear movement experiment.

4.4 Experiment 2

The second experiment focused on demonstrating the individual motion as nonlinear movement in the laboratory environment. For designing this experiment, one table (size: 1.2m x 0.6 m approx) was also employed as an interacted object with personal activity and same quantity (4) of UHF RFID passive tags that were utilized for conducting the linear movement. Moreover, the RFID reader configuration, e.g. reading rate and power, was the same as described in the initial experiment. The reader interval frequency was also set to five times per second. The RFID tags were labelled with the personalized ID which is similar to those used for presenting linear movement. However, the significant difference from the second experiment was the user's walking route. Because the activity undertaken by the user in this experiment was set in a scenario of nonlinear movement, the placement of the RFID tags should not be put on an object in the same direction. In the first experiment, four RFID tags were located linearly on the same side of a table. However, all RFID tags were mounted on each middle line of four table sides respectively in the second experiment. In addition, these tags were located vertically over the edge of the table. After positioning the RFID tags, the user was equipped with a RFID reader in order to collect the information of RFID tag involved in this certain personal motion. Particularly, the user started walking from tag T1, and then sequentially passed tags T2, T3, T4 and finally came back to tag T1. According to this particular activity, the start point and end point was only marked as per tag T1 in the second experiment. For completing the nonlinear movement, the user was required to walk around the table in a predefined route which were five times track in a clock manner. After each track, the RFID reader was switched off and connected to the workstation. Finally, the original RFID dataset was downloaded from the RFID reader and saved in a specified directory of the workstation. The scenario of nonlinear movement is shown in Figure 4.12.

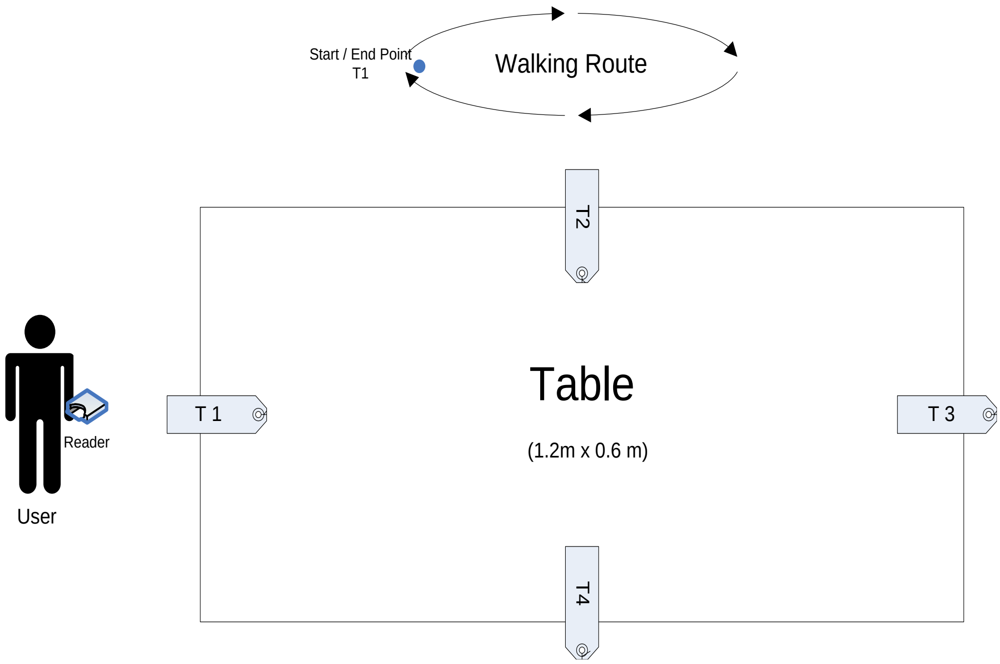


Figure 4.12: Nonlinear Movement

4.4.1 Experiment 2 Result

The individual activity in this experiment was a set of five circumnavigations of the table as a person took the RFID reader and walked around the table in a preset direction. The RFID reader was switched off and connected to the workstation to generate the RFID dataset at the end of each track. Finally, there were five datasets produced in this experiment. The original dataset was converted by extracting the relevant tag ID and time log, which followed the process of customizing the raw RFID dataset as discussed in the first experiment. The start point and end point of this nonlinear movement was only symbolized by the tag T1. As a result, the personalized RFID dataset started with T1 and ended with T1 (See Table 4.7). The raw dataset and customized dataset of each track in this experiment are presented in Appendix C and Appendix D.

Time Log	Assigned Tag ID
9:19:24	T1
9:19:25	T1
9:19:26	T2
9:19:26	T4
9:19:26	T1
9:19:26	T1
9:19:26	T2
9:19:27	T3
9:19:27	T1
9:19:28	T3
9:19:28	T2
9:19:28	T3
9:19:28	T2
9:19:29	T2
9:19:29	T3
9:19:30	T3
9:19:31	T4
9:19:31	T3
9:19:31	T4
9:19:32	T4
9:19:32	T3
9:19:33	T4
9:19:33	T4
9:19:34	T4
9:19:34	T1
9:19:35	T4
9:19:35	T1
9:19:36	T1

Table 4.7: The Sample of Customized Dataset of Nonlinear Movement

Time Log	Assigned Tag ID
9:19:24	T1
9:19:25	T1
9:19:26	T2
9:19:26	T4
9:19:26	T1
9:19:26	T1
9:19:26	T2
9:19:27	T3
9:19:27	T1
9:19:28	T3
9:19:28	T2
9:19:28	T3
9:19:28	T2
9:19:29	T2
9:19:29	T3
9:19:30	T3
9:19:31	T4
9:19:31	T3
9:19:31	T4
9:19:32	T4
9:19:32	T3
9:19:33	T4
9:19:33	T4
9:19:34	T4
9:19:34	T1
9:19:35	T4
9:19:35	T1
9:19:36	T1

Table 4.8: The Sample of Overlapping Time of Different Tags

The first experiment result points out the time log of different tags were overlapped in the RFID dataset. Likewise, the dataset of the nonlinear movement contains the similar problem as different tags were sensed by the RFID reader at the same time. The RFID reader seemed to have picked up the signals from two different tags at the same time in the first experiment. However, in the nonlinear movement, the RFID tag was able to record more than two tags at one time (See Table 4.8). According to the time log of each RFID tag, five tracks of nonlinear movement can be represented by five series of RFID data array which are shown in Table 4.9.

Track Number	Tag Sequence
1	{T1, T2, T2, T1, T1, T1, T2, T2, T3, T2, T2, T3, T2, T3, T2, T2, T4, T2, T2, T3, T4, T2, T3, T3, T2, T4, T4, T2, T3, T3, T4, T4, T3, T3, T4, T4, T3, T4, T1 ,T2, T2 ,T4, T4, T4 , T1, T1, T4, T4, T1, T4, T4, T1, T4, T4, T1}
2	{T1, T1, T2, T4, T1, T1, T2, T3, T1, T3, T2, T3, T2, T2, T3, T3, T4, T3, T4, T4, T3, T4, T4, T4, T1, T4, T1, T1}
3	{T1, T2, T4, T1, T2, T4, T2, T4, T4, T1, T2, T2, T2, T3, T4, T2, T3, T2, T3, T4, T4, T2, T3, T4, T3, T4, T3, T4, T3, T3, T4, T1, T3, T4, T1, T4, T1, T4, T1, T4, T1}
4	{T1, T4, T1, T4, T1, T2, T4, T1, T2, T2, T3, T2, T1, T2, T3, T2, T4, T3, T3, T4, T2, T3, T4, T3, T4, T3, T4, T3, T4, T1, T2, T4, T3, T1, T4, T4, T1, T1, T4, T1, T4, T1}
5	{T1, T2, T2, T1, T2, T4, T1, T4, T1, T2, T2, T3, T4, T3, T2, T2, T3, T3, T2, T3, T3, T4, T3, T4, T3, T4, T3, T3, T4, T1, T4, T4, T1, T4, T1, T1}

Table 4.9: Tag Sequences of Nonlinear Movement

The purpose of conducting this second experiment is to perform a nonlinear personal activity. The user was required to walk around the table in a clockwise manner as passing the RFID tags T1, T2, T3, T4, and ending the movement by coming back the tag T1. Therefore, every single RFID tag is considered to be the landmark for constructing walking route. In theory, this nonlinear movement represented by the RFID data sequence tends to be in an array such as: {T1, T2, T3, T4, T1} or {T1…T1, T2…T2, T3…T3, T4…T4, T1…T1}. As noted in the first experiment result, T1, T2, T3, and T4 are seen as the four independent groups which must contain the same value and must be followed by each other in a certain order. Unfortunately, the RFID dataset generated from each track is unable to match the theoretical data sequence. Comparing with the standard sequence, the walking route presented in these five data sequence is totally different from the predefined one. By taking the dataset of the 2nd track for example, the user begins walking from tag T1 to T2; back to T1 passing T4 at the beginning to continue on walking to T2 and then back again to T1 finishing at T3 in the first four seconds. This is not the correct activity undertaken by the user in the second experiment. In order to analyse the difference of the walking route between the standard one and those marked by the RFID sequence, the standard dataset and experimental datasets were all visualized by defining X axis and Y axis as the two demission for locating each tag on the table (See the following figures).

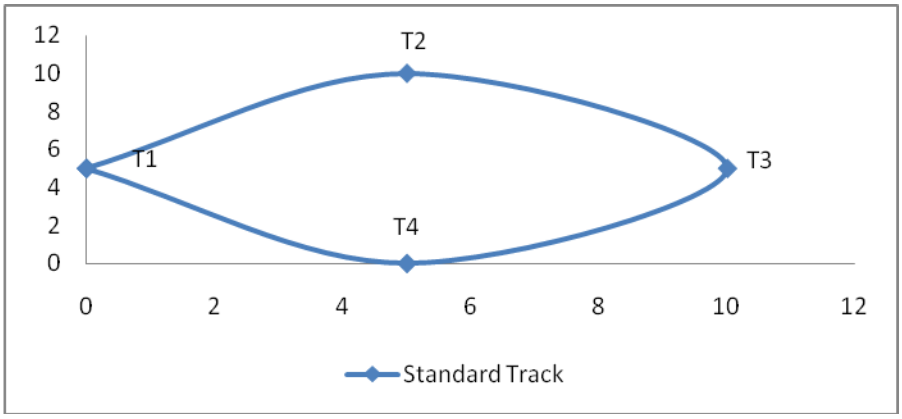


Figure 4.13: Standard Track

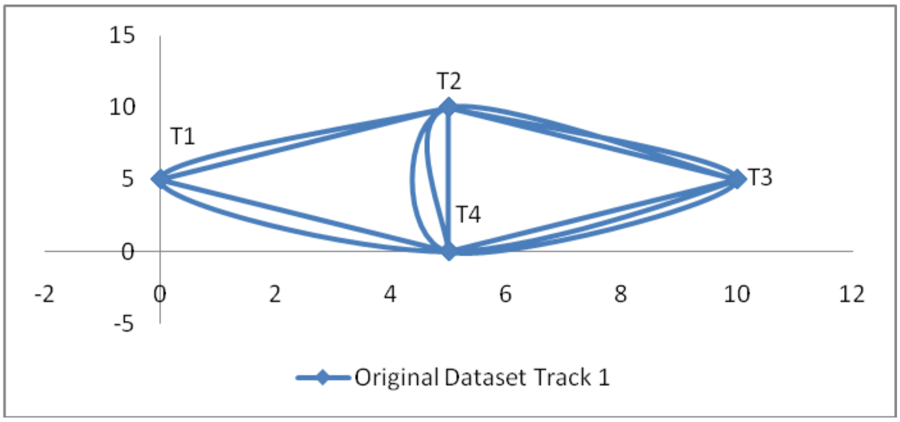


Figure 4.14: 1st Track of Nonlinear Movment

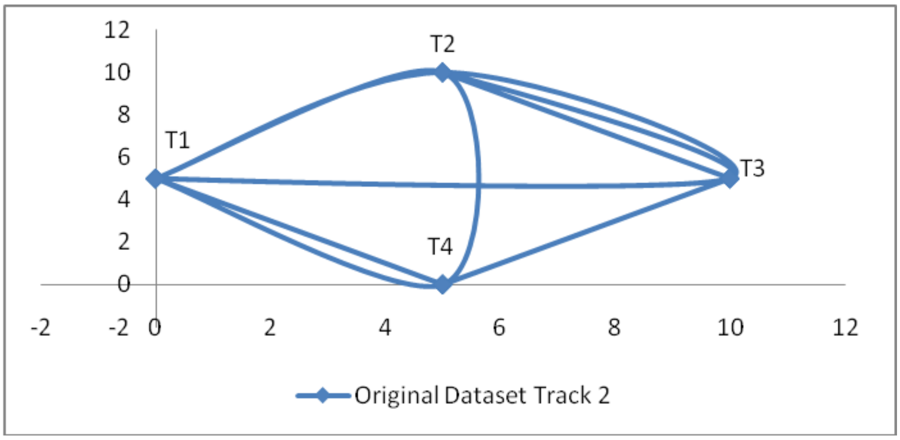


Figure 4.15: 2nd track of Nonlinear Movment

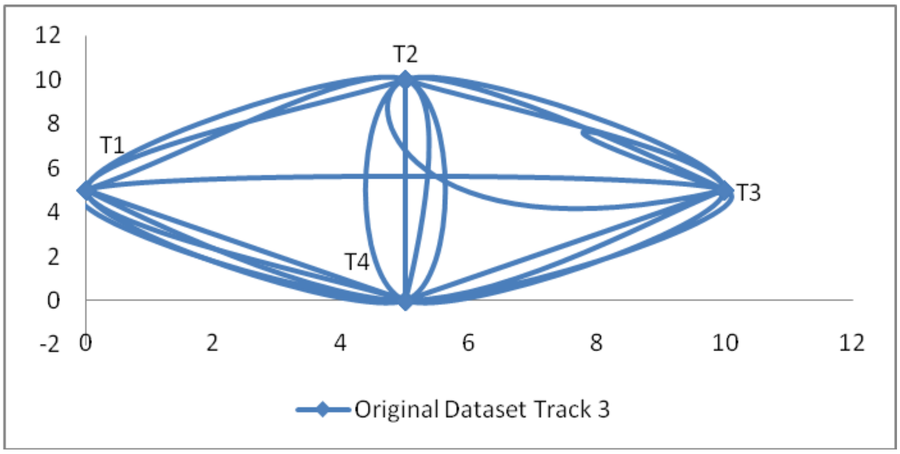


Figure 4.16: 3rd Track of Nonlinear Movment

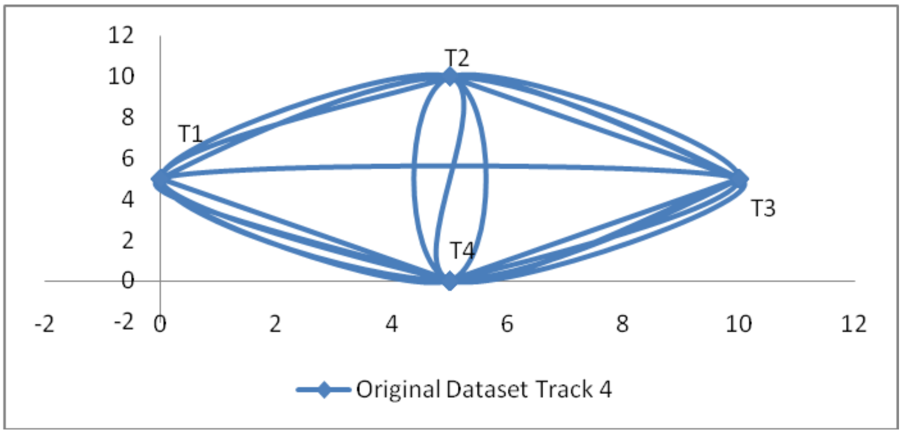


Figure 4.17: 4th Track of Nonlinear Movement

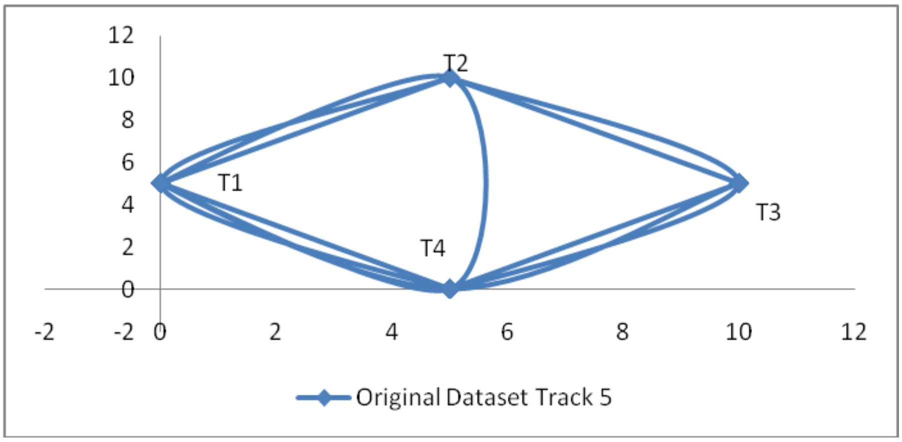


Figure 4.18: 5^{th} Track of Nonlinear Movement

The five figures above present the problem involved in these RFID datasets. The detected walking route of all five tracks was represented by the relevant RFID dataset includes the major difference to the predefined direction and obviously varies between each other. As mentioned before, several RFID tags may be recorded by the RFID reader at the same time during the experiment process. It leads to difficulty when distinguishing the exact tag that the user passed by. As a consequence, the RFID dataset of both experiments appeared to be too noisy to indicate the specific personal activity. On the other hand, using the RFID dataset to infer the personal activity is based on analysing the accurate data sequence. The unreliable information involved in the RFID dataset results in the confusion of determining the certain activity. Thus, an appropriate method needs to be carried out for filtering the incorrect data in the RFID data stream. Attempts to do this are described in the next chapter.

Chapter 5

Data Pre-processing and Analysis

The unreliability of RFID detection devices has limited the integration of the RIFD technology within the enterprise. A significant problem that emerged in RFID devices was that the system can not reliably read the information of the time in the real world deployment accurately (Feder, 2004). The accurate reading rate that was discovered in commercial application used by the supplier or retailers was normally between 60% and 70% (Sullivan, 2005). The reliability of the data stream which was generated from RFID systems had been highlighted by many researchers. However, the main factor triggering the uncertainty in the RFID data stream was investigated and concluded by researchers to be false reads occurring during the time when the RFID reader detect the RFID tags (Brusey et al., 2003 & Fishkin et al., 2005 & Jeffery, et al., 2006, Kim et al., 2007). In particular, the false reads are classified into two major categories, which are false positive reads and false negative reads. Generally speaking, false negative reads occur when RFID tags might not be read inside the region, resulting in the mistaken belief that the object is not present. Furthermore, the false positive reads appear where RFID tags might be detected outside the region, leading to a false belief that the object is present (Brusey et al., 2003).

Both experiment results of this research show that various RFID tags were recorded at the same time by the RFID reader in a laboratory environment. The reader captured the signal reflecting from several nearby tags while the user was standing near a certain tag during the activity performance. For instance, the reader in the experiment of linear movement recorded the tags T8 and T5 at the same time in the first track where the user completed the activity passing the T5. The second experiment indicates that the reader recorded more than two tags per second through the entire nonlinear movement. These noisy data displayed in the same time series are seen as false reads in the RFID dataset. Additionally, these noise detected in two experiments were all classified as the false positive reads based on the inspection that tags were read outside the region. The false positive reads are considered to have a negative effect on the inference of individual activity. Rao et al (2006) stated that a small quantity of false reads was able to produce large error in analytical result. As mentioned earlier in 4.4.1 Experiment 2 Result, the noisy data involved in the original RFID data stream resulted in the difficulty for researchers to determine the walking route the user had used. In order to conduct a proper individual activity inference by using RFID tag sequence, the dirty data is required to be pre-processed. Thus, an adaptive data clean method needs to be carried out for reducing the uncertainty of the raw RFID sequence.

5.1 Previous Data Pre-processing Methods

There are several methods that were proposed in cleansing the dirty RFID dataset in the preceding literatures. A deferred cleaning method was introduced to deal with the anomalies in the RFID reads. This method extended SQL-TS language to provide a specified rule for cleaning the data sequence (Rao et al., 2006). However, most RFID middleware system utilized the Smoothing Filter to get rid of the inherent unreliability of RFID data sequence. As a frequently used mechanism for cleaning the RFID dataset, the Temporal Smoothing Filter employed a sliding window to reinstate the missing reading produced by the RFID reader (Gupta et al., 2004). This smoothing window approach enhanced the ability of reader on sensing the tags, therefore reduces the false negative reads. Moreover, Jeffery et al. (2006) modified the traditional temporal window method and created a new smooth filter: Statistical sMoothing for Unreliable RFID data (SMURF). SMURF consisted of a sliding window processor for smoothing the raw RFID data stream and an improved mechanism for ensuring the efficiency of data clean. For cleaning the single tag reading, SMURF provided a binomial sampling model by viewing each epoch as an independent trial. While in the process of multi-tag cleaning, a random sampling model and estimator was adopted by organizing several epochs in a window size. The window size was adjusted to filter the noise by using the algorithm of Additive-Increase/Multiplicative-Decrease (AIMD). Then again, standard statistical analysis proposed an efficient approach for many applications in reducing both false negative and positive reads. In the Smart Medicine Cabinet, the false read resulted in a flickering problem appeared on the graphical user interface (Floerkemeier et al., 2003). This issue was addressed by Brusey et al (2003) who suggested a top-hat function would be useful to deal with the flickering phenomenon in the Smart Medicine Cabinet. The combination of using both top-hat and Gaussian methods was applied in reducing false positive reads came out in the process of stack reading (McFarlane, 2002 & Brusey et al., 2003). The simple left-right Hidden Markov Models was applied in inferring the activity by specifying the sequence of steps for each activity and the probability of the interaction with individual objects in each step. In this approach, both negative and positive reads were able to be accounted for using the Markov Chains Model (Fishkin et al., 2005).

5.2 Proposed Data Pre-processing Method 1 and Analysis

The methods proposed in the previous research for filtering the RFID data stream indicates that RFID data time series and standard statistical algorithm are two essential components for constructing the adaptive RFID data clean mechanism. Therefore, the first important step of removing the noisiness from the RFID data sequence is to determine the relevant time series of every single data point. By examining all datasets generated from two experiments in this research, it is found the same tag was detected by the reader within one second as well as different tags appeared in the same time series. In this case, an epoch was created from the raw RFID data sequence at every second. Given the raw RFID dataset which was assigned with time log and tag ID, it is able to mark the time series of each data. To function the epoch into initial dataset, both same tags and different tags that were detected by the reader at the same time were highlighted in various colours (See Table 5.1).

Time Log	Assigned Tag ID
0:22:02	T9
0:22:03	T9
0:22:03	T9
0:22:04	T9
0:22:05	T9
0:22:05	T9
0:22:06	T6
0:22:06	T6
0:22:07	T6
0:22:08	T6
0:22:10	T8
0:22:10	T8
0:22:11	T8
0:22:12	T8
0:22:12	T8
0:22:15	T5
0:22:16	T8
0:22:16	T5
0:22:16	T5
0:22:17	T5

Table 5.1: The sample of Different Tags in an Epoch

5.2.1 Method 1

Using the datasets of the first experiment, the same tag was recorded by the reader several times per second. Only a few different tags were shown within one second and the quantity of them was no more than two. Thus, a simple majority voting method is considered as efficient for removing the noisy data from these five datasets, if a suitable epoch period is selected. The majority voting is the widely used decision rule in practice. It is the simplest scheme which generates the same effect to those more complicated methods on improving the recognition results (Lam et al., 1997). In the majority voting process, it is a common that a campaigner or a group who gets more than half votes than the others wins the election. If there are two candidates X and Y for the voters in practice, it seems that X defeats Y when the quantity of votes for X is greater than the number of votes for Y (Garcia-Lapresta, 2005). According to this approach, each epoch taken from the raw dataset was processed by using the rule of majority voting. Consequently, the minority group of tags was deleted whereas the majority tag was saved in the dataset. If there were several of the same tags in an epoch, only one tag was chosen to represent the others. If there were several different tags in an epoch, only one tag or one set of tags who won the majority vote was maintained in one epoch (See Table 5.2). In order to accurately infer the personal activity, the majority voting method was applied in removing the noisy data from the datasets of both experiments. The pre-processed datasets were shown in Appendix E and Appendix F.

Time Log	Assigned Tag ID	Majority Voting
0:22:02	T9	T9
0:22:03	T9	T9
0:22:03	T9	
0:22:04	T9	T9
0:22:05	T9	T9
0:22:05	T9	
0:22:06	T6	T6
0:22:06	T6	
0:22:07	T6	T6
0:22:08	T6	T6
0:22:10	T8	T8
0:22:10	T8	
0:22:11	T8	T8
0:22:12	T8	T8
0:22:12	T8	
0:22:15	T5	T5
0:22:16	T8	
0:22:16	T5	T5
0:22:16	T5	
0:22:17	T5	

Table 5.2: The Sample of Dataset Processed by Majority Voting

5.2.2 Data Analysis of Method 1

Taking the each tag ID from the epoch after filtering process and arraying them based on their time manner, the pre-processed dataset of the first experiment is presented in each array (See table 5.3).

Track Number	Tag Sequence
1	{T9, T9, T9, T9, T6, T6, T6, T8, T8, T8, T5, T5}
2	{T9, T9, T9, T6, T6, T6, T8, T8, T8, T5, T5, T5}
3	{T9, T9, T9, T9, T9, T9, T6, T6, T6, T8, T8, T5, T5}
4	{T9, T9, T9, T9, T6, T6, T6, T8, T8, T8, T8,}
5	{T9, T9, T9, T9, T9, T6, T6, T6, T6, T6, T8, T8, T8, T5, T5, T5}

Table 5.3: Tag Sequences of the First Experiment (Filtered by Majority Voting)

Observing these five datasets which were cleaned by using the majority voting approach, it is rather possible to make a conclusion that all of these filtered datasets follow a same sequence format as T9…T9, T6...T6, T8...T8, T5…T5. As mentioned in the previous chapter, the individual activity in the initial experiment was a linear movement as the user sequentially passed four RFID tags in a predefined route by holding a RFID reader. Ideally, the dataset generated by the RFID system would be in the same order to this predefined sequence such as: T9, T6, T8, T5 or T9…T9, T6...T6, T8...T8, T5…T5. Moreover, each data in this array is considered to be an independent group which consisted of coherent values. Comparing the pre-processed dataset with the theoretical one, it shows that all datasets of first experiment which were filtered by using the method of majority voting contain the 100% of similarity to the theoretical one. Since the majority voting method is efficient for removing the irrelevant tag ID in the first experiment, it was utilized to clean the noisy data from the dataset of second experiment. By arraying the data taken from filtered dataset of the second experiment, the activity of each track is organized in Table 5.4.

Track Number	Tag Sequence
1	{T1, T2, T1, T1, T2, T2, T2, T3, T2, T2, T2, T3, T4, T2, T3, T2, T4, T4, T2, T3, T4, T3, T3, T4, T4, T1, T2, T4, T4, T1, T1, T4, T4, T4, T1, T4, T1}
2	{T1, T1, T2, T1, T1, T2, T3, T1, T3, T2, T2, T3, T3, T4, T4, T3, T4, T4, T1, T4, T1, T1}
3	{T1, T2, T4, T1, T2, T4, T2, T4, T4, T1, T2, T2, T3, T4, T2, T3, T4, T2, T3, T4, T3, T4, T3, T4 T3, T3, T4, T1, T4, T1, T4, T1}
4	{T1, T4, T1, T2, T4, T1, T2, T3, T2, T1, T2, T3, T2, T4 , T3, T3, T4, T2, T3, T4, T3, T4, T3, T4, T1, T4, T4, T1, T1, T4, T1}
5	{T1, T2, T2, T1, T2, T4, T1, T4, T1, T2, T2, T3, T2, T3, T3, T4, T3, T4, T3, T4, T4, T1, T1}

Table 5.4: Tag Sequences of the Second Experiment (Filtered by Majority Voting)

In the second experiment, a user demonstrated the nonlinear movement by passing four RFID tags around the table. The walking route of this personal activity was set in a clockwise manner as the user started walking from the tag T1; separately and in order moved to the tags t2, t3, t4; and finally came back the tag T1. Therefore, the walking route of nonlinear movement was defined in the order of T1, T2, T3, T4, T1. Likewise, the dataset generated from each track was expected to present the sequence like T1, T2, T3, T4, T1 or T1…T1, T2…T2, T3…T3, T4…T4, T1…T1. By exploring five datasets listed above, it is clear that none of them are able to present the same walking route where the user actually passed in this experiment. In order to have a comparison with the raw dataset, these five cleaned data sequences are visualized into several diagrams as follows:

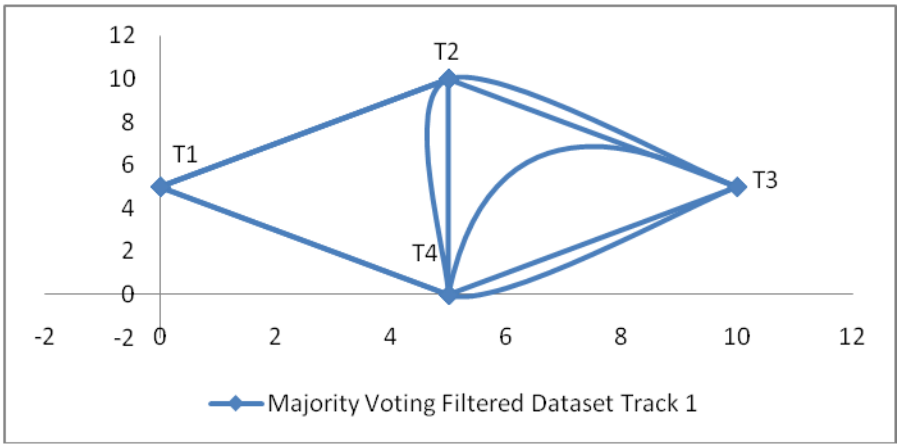


Figure 5.1 : 1st Track of Nonlinear Movement (Filtered by Majority Voting)

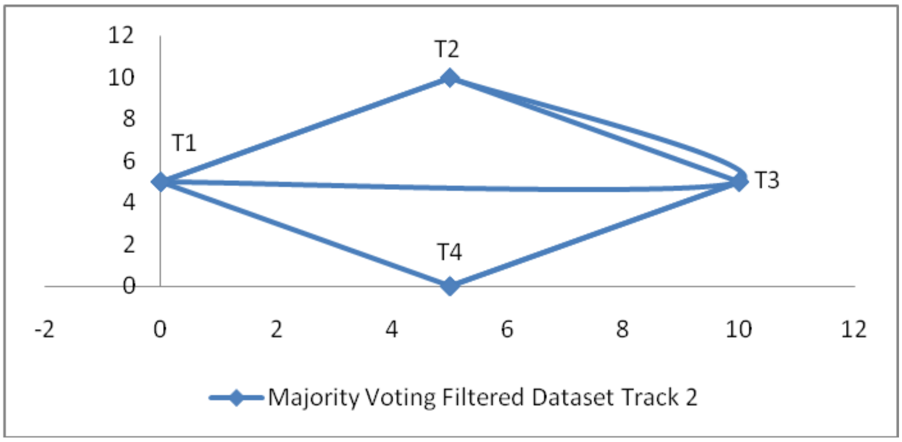


Figure 5.2 : 2nd Track of Nonlinear Movement (Filtered by Majority Voting)

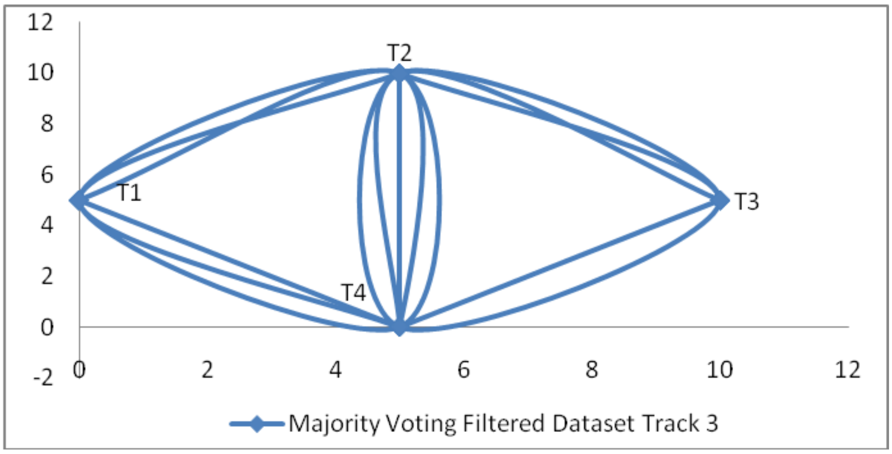


Figure5.3 : 3rd Track of Nonlinear Movement (Filtered by Majority Voting)

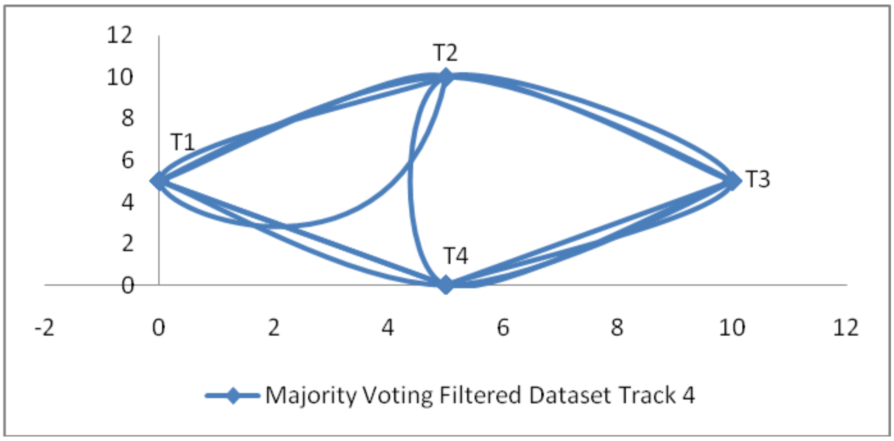


Figure 5.4: 4th Track of Nonlinear Movement (Filtered by Majority Voting)

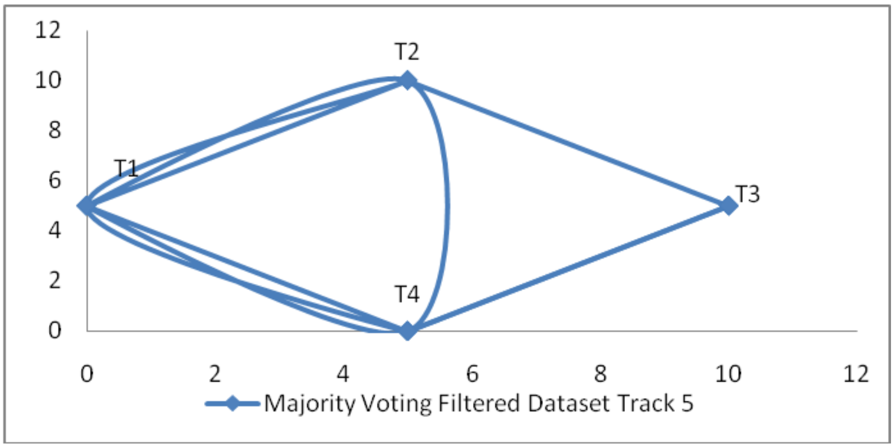


Figure 5.5: 5th Track of Nonlinear Movement (Filtered by Majority Voting)

These five figures illustrate the walking route which was generated from each pre-processed dataset of the second experiment. Comparing the walking route with those presented in the uncleaned dataset, the dataset seems to have less complexity after the first level filtering. In addition, there is a tendency that false reads appearing in the RFID data stream of the second experiment were reduced by using the majority voting method. However, it is still obvious that these pre-processed datasets are not clean enough for the personal activity inference because none of them are able to present a similar direction to the predefined waking route. In other words, the majority voting method is not as efficient as it was applied in dealing with the noisy data produced by linear movement. Thus, a statistical algorithm is considered to be required for the second level filtering.

5.3 Proposed Data Pre-processing Method 2 and Analysis

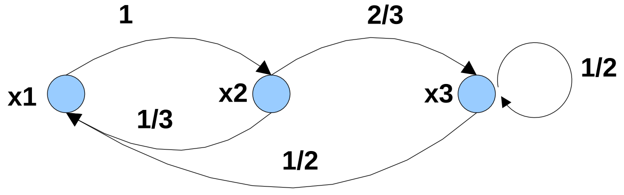
Existing statistical algorithms for cleaning the raw RFID data stream have been investigated by the previous researches, such as a top-hat function for cleaning the missed reads in the Smart Medicine Cabinet, Gaussian function for filtering the false reads in the stack control and the Hidden Markov Model for solving both false negative and positive reads emerging in the RFID system (Mc-Farlane, 2002 & Brusey et al., 2003 & Fishkin et al., 2005). In this research, the standard algorithm of Markov Chains was employed to conduct the second level data pre-processing.

5.3.1 Method 2

A Markov Chain is a stochastic process that includes a series of random variable $X_{.1}, X_2 ... X_{n+1}$. It is used to calculate the probability of these random variables in the sequence (Pankin, 1987). The transition probability is usually presented in the format as a matrix (See Figure 5.6). The matrix $X(n, n+1)$ means the probability that, given the present state is n, the process will be in state $n+1$ in the next time unit. The standard algorithm of transition probability in the Markov Chain is shown as:

$$\Pr(X_{n+1} = x \mid X_n = x_n, ..., X_1 = x_1) = \Pr(X_{n+1} = x \mid X_n = x_n)$$

where X_n is the current state and X_{n+1} the future state. Given the transition probability of current step X_n the transition probability of next step X_{n+1} is able to be computed as n+1's power of transition probability matrix (Lin et al., 2006).



	x1	x2	x3
x1	0	1	0
x2	1/3	0	2/3
x3	1/2	0	1/2

Figure 5.6: A Markov Chain and Its Transition Probability Matrix (Lin et al., 2006)

Markov Chains are a type of useful data analytical model which has been integrated in various applications for evaluating variable bit rate (VBR) video traffic (Chiruvolu et al., 1998), monitoring the changing trends in health status of an elderly person (Kaushik, 2005) and analysing customer behaviour model graph (CBMG) in the e-commerce circumstance (Mark & Scaba, 2007). However, the major use of Makovian models tends to be in the bioinformatics research, which is specified in exploring the genetic data sequence. Dalevi and Dubhashi (2005) developed an application for reducing the noisy data in DNA sequence by extending Peres-Shields Estimator (PS) to Variable Length Markov Chains (VLMC). Deng et al. (2005) proposed a Markov Chains Cluster (MCC) for solving the similar and dynamic genes in the gene expression dataset. Heath and Pati (2007) conducted a research of analysing genomic sequence by using a Markov Chain Model to estimate the transition probabilities of data at different scales.

The previous literature indicates that the main purpose of employing the Markov Chains Model for data analysis is to calculate the transition probability of each variable in the data sequence. In this research, the activity undertaken by the user can be seen as a type of continuous movement. Moreover, each data point was treated as an independent unit in the data sequence. From this point of view, the transition probability from one tag to the other tags is considered to be a crucial factor for the personal activity inference. Therefore, using the algorithm of Markov Chains for calculating the transition probability of each tag in the RFID datasets is an indispensable stage to calculate personal activity in the second experiment. To accomplish the Markov Chains computing, the Discussion Analysis Tool (DAT) was utilized to calculate the transition probability of the variables in the data sequence. According to Jeong (2003), DAT is a sequential analysis tool designed for the quantitative analysis of event sequence, which was programmed into Microsoft Excel by using Visual Basic. At the same time, DAT is able to measure the event sequence and provide the transitional probabilities in the threaded discussions as well as recognizing patterns in human-computer interactions. Here in this research, the new release beta version of DAT v1.79 was utilized to perform the sequence analysis (See Figure 5.7).

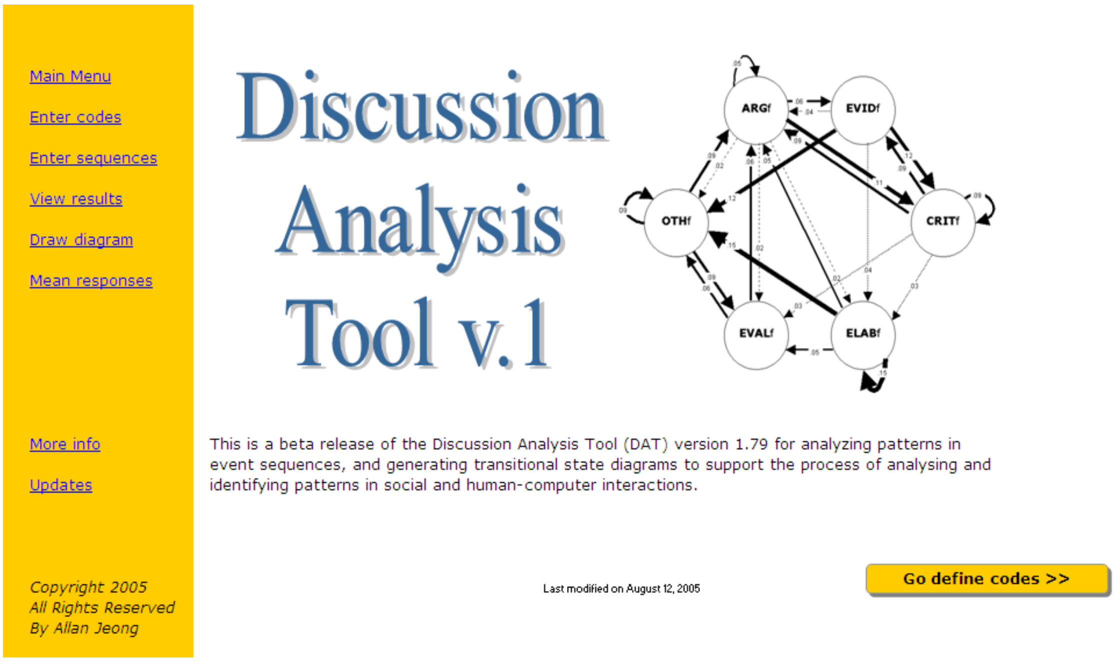


Figure 5.7: Discussion Analysis Tool v1.79 (Jeong, 2005)

5.3.2 Data Analysis of Method 2

Before running the calculation of transition probability, DAT requires the user to define codes (variables) and codes sequence (data index) in one dataset. As five data sequences of the second experiment were all represented by four RFID tags, the code was defined as these four tags' ID: T1, T2, T3 and T4. To locate code sequence, the index number of each variable was examined in the dataset. All data were arrayed by following their relevant time log and each data was set to be independent from each other. Hence, the index number is equal to the order of each tag ID in the data stream. The index number of one sequence can be seen as an array which consisted of a group of the gradual numbers. As a result, the code sequence of each dataset starts with 1 and finishes with the number of the length of one certain array. Taking the dataset of the second track for example, the index number for each data in {T1, T1, T2, T1, T1, T2, T3, T1, T3, T2, T2, T3, T3, T4, T4, T3, T4, T4, T1, T4, T1, T1} is presented as {1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22}. After defining the code and code sequence, the transition probability of each tag in the data sequence was automatically computed and formatted in a matrix (See the following tables).

Transitional Probabilities Matrix				
	T1	T2	T3	T4
T1	0.29	0.43	0	0.29
T2	0.1	0.4	0.3	0.2
T3	0	0.33	0.17	0.5
T4	0.31	0.08	0.15	0.46

Table 5.5: Transitional Probabilities Matrix of 1st Track Dataset

The transitional probability of the dataset in the first track (Table 5.3) shows that T1 has highest transitional probability of 43% to T2 whereas the T3 has 33% of probability to T2. T2 has 40% of possibility of staying in the same position however contains 30% of possibility of moving to T3. The transitional possibility from T3 to T4 (50%) is higher than the situation of T3 to T2 (33%). T4 has a second highest transitional probability as moving to T1 while the top value of transitional probability from T4 to T4 is 46%.

Transitional Probabilities Matrix				
	T1	T2	T3	T4
T1	0.43	0.29	0.14	0.14
T2	0.25	0.25	0.5	0
T3	0.2	0.2	0.2	0.4
T4	0.4	0	0.2	0.4

Table 5.6: Transitional Probabilities Matrix of 2nd Track Dataset

The second track (Table 5.4) presents the transitional probability of T1 to T2 is 29%, which is the second highest value compared with the 43% of transitional probability of T1 to T1. It is rather possible for T2 to shift to T3 as its highest transitional probability is 50%. T3 contains the same probabilities (20%) of moving to T1, T2, and T3, however, it is more likely for T3 to transfer to T4 as the 40% of transitional probability. The transitional probability of T4 to T1 is as high as the one of T4 to T4, which are both calculated as 40%.

Transitional Probabilities Matrix				
	T1	T2	T3	T4
T1	0	0.6	0	0.4
T2	0	0.14	0.43	0.43
T3	0	0	0.14	0.86
T4	0.42	0.25	0.25	0.08

Table 5.7: Transitional Probabilities Matrix of 3rd Track Dataset

The matrix of transitional probabilities of third track (Table 5.5) indicates T1 prefers moving to T2 rather than jumping to T4. There is the same transitional probability of T2 to T3 and T2 to T4. T3 has a significant highest transitional probability of heading to T4 (86%). The highest transitional probability of T4 is 42% when it moves towards to T1.

Transitional Probabilities Matrix				
	T1	T2	T3	T4
T1	0.14	0.43	0	0.43
T2	0.17	0	0.5	0.33
T3	0	0.29	0.14	0.57
T4	0.5	0.1	0.3	0.1

Table 5.8: Transitional Probabilities Matrix of 4thTrack Dataset

The Highest transitional probability of T1 in the fourth track (Table 5.6) is 43%, where the same probability occurred in the situation that T1 either moves to T2 or T4. T2 has the highest transitional probability (50%) of running to T3 as well as the one shown in a matrix of T4 to T1. T3 contains the 57% of highest probability of transferring to T4.

Transitional Probabilities Matrix				
	T1	T2	T3	T4
T1	0	0.6	0	0.4
T2	0.17	0.33	0.33	0.17
T3	0	0.2	0.2	0.6
T4	0.5	0	0.33	0.17

Table 5.9: Transitional Probabilities Matrix of 5^{th} Track Dataset

It is clear that the transitional probability of T1 to T2 is higher than the situation of T1 to T4 in the fifth track (Table 5.7). The transitional probability of T2 to T1 is as lower as the way of T2 to T4, which is estimated as only 17%. While the highest transitional probability of T2 is counted as 33% when it moves to T3 or either stays in T2. T3 to T4 has a significant higher transitional probability than the others. Similarly, the transitional probability of T4 to T1 is also obviously greater than those scenarios of T4 to T3, or T4 to T4.

To sum up, these five tables comprehensively describe both highest and lowest transitional probability of each tag in 5 datasets of nonlinear movement. Depending on the highest transitional probability of each tag, it can be used to figure out the most possible movement from one tag to the others. The activity undertaken by the person seems to be determined. In order to map the relation between these variables, modelling the transitional probabilities into a visual diagram is considered to be an effective approach. Hence, each matrix of transitional probabilities that were computed from above five dataset was converted into five diagrams by using DAT drawing tool. In these five models, fours tags were presented by four individual circles. The arrow points out the direction between these four tags with the calculated transitional probabilities. Each transitional probabilities model of these five data sequences is shown as follows:

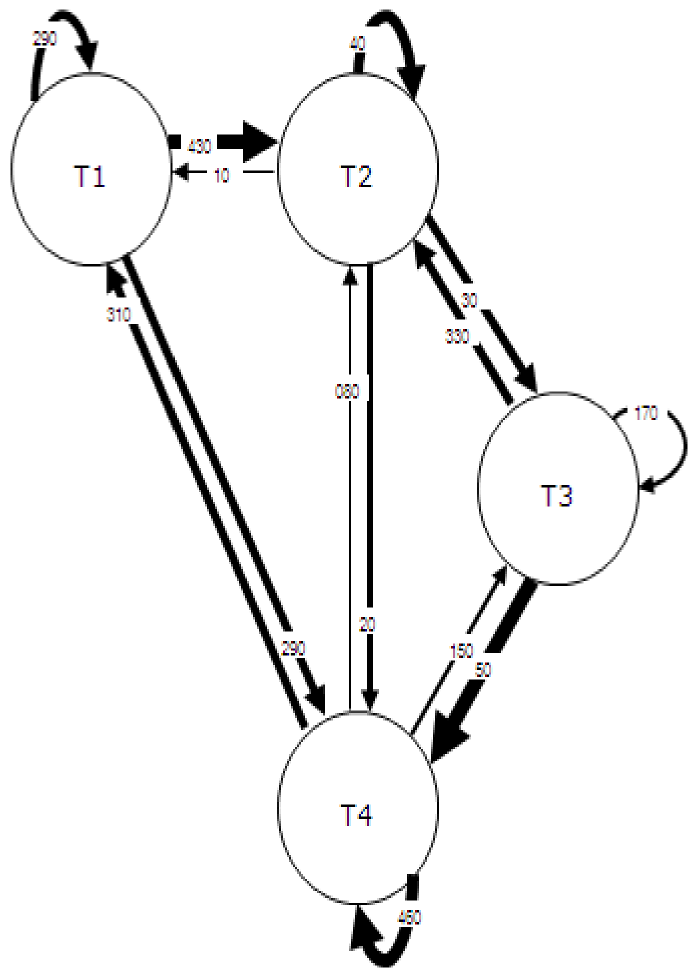


Figure 5.8: Transitional Probabilities Model of 1st Track Dataset

By examining the transitional probabilities in the first model (Figure 5.8), it is not difficult to find that the most possible lane to T2 is from T1. T2 has the highest probability to T3 excepting the situation of remaining in the same position of T2. T3 is most likely to transfer to T4. It is possible for T4 to reach T1 if there is no whirling situation found in T4.

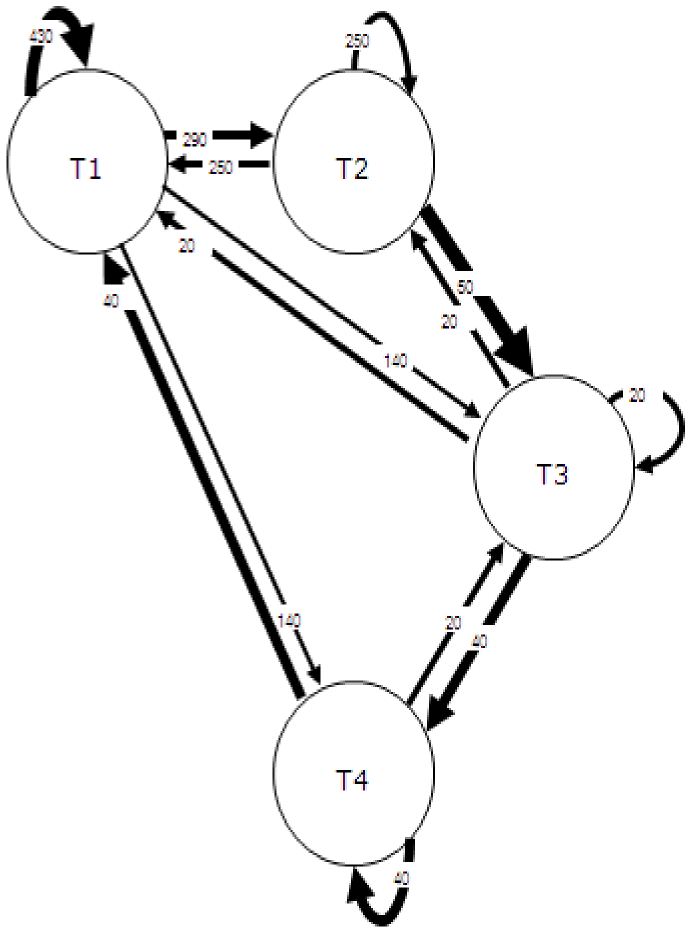


Figure: 5.9: Transitional Probabilities Model of 2nd Track Dataset

The most obvious route emerging in the second model (Figure 5.9) can be seen as T2 to T3, and T3 to T4. Excepting the situation that T1 returns to itself, it is quite possible to find the route to T2 is from T1. Compared with the direction from T4 to T3, when the user is at T4 he seems more likely to be either staying at the same location or transferring to T1.

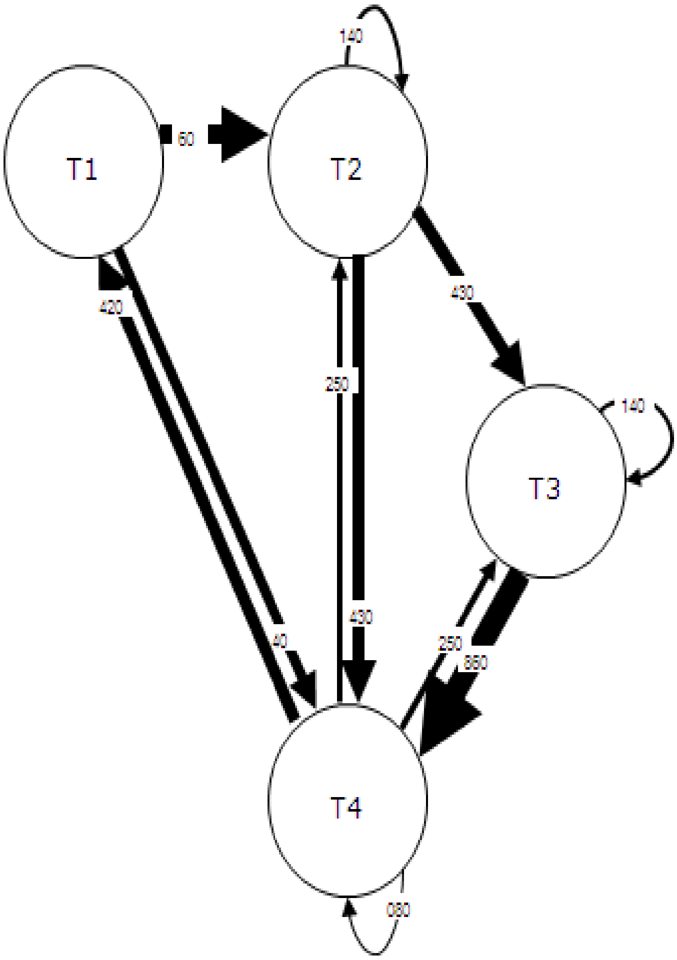


Figure 5.10: Transitional Probabilities Model of 3rd Track Dataset

There are two directions which are considered to be the most significant transitional path in the third model (Figure 5.10): T1 to T2 and T3 to T4. Interestingly, however, the user at T2 also seems to be able to transfer to T4 with the same probability existing in the route of T2 to T3. There is also another alternative way to T4 presenting in this model, which is from T1 with its second highest transitional probability.

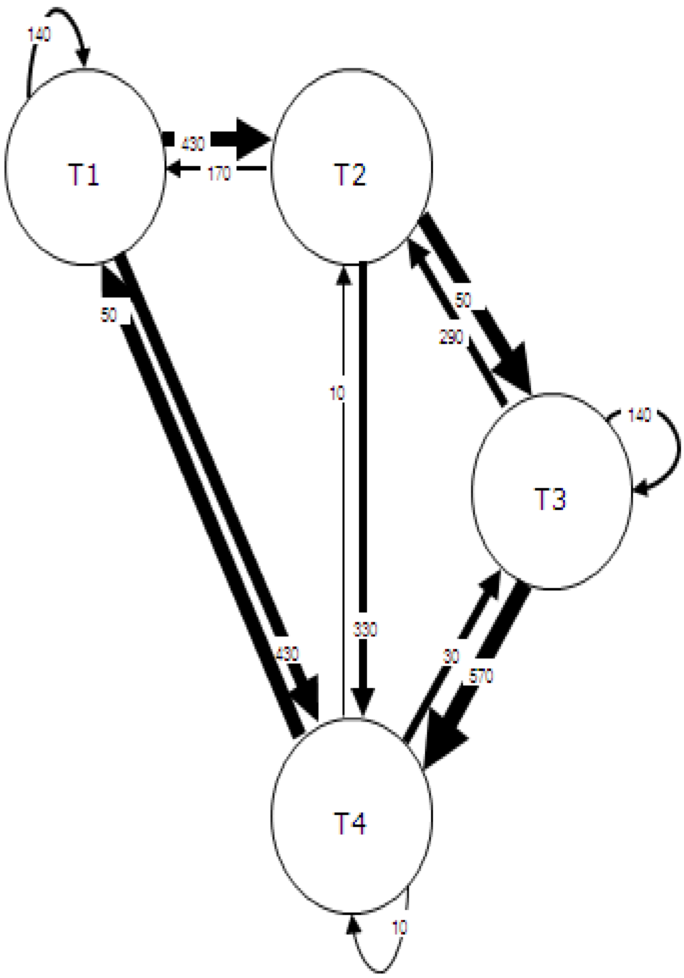


Figure 5.11: Transitional Probabilities Model of 4th Track Dataset

The most possible transitional orders presenting in the fourth model (Figure 5.11) can be seen as T2 to t3, T3 to T4 and T4 to T1. However, T1 seems to either transfer to T4 or T2 due to the same transitional probability which was calculated based on the route of T1 to T4 and T1 to T2.

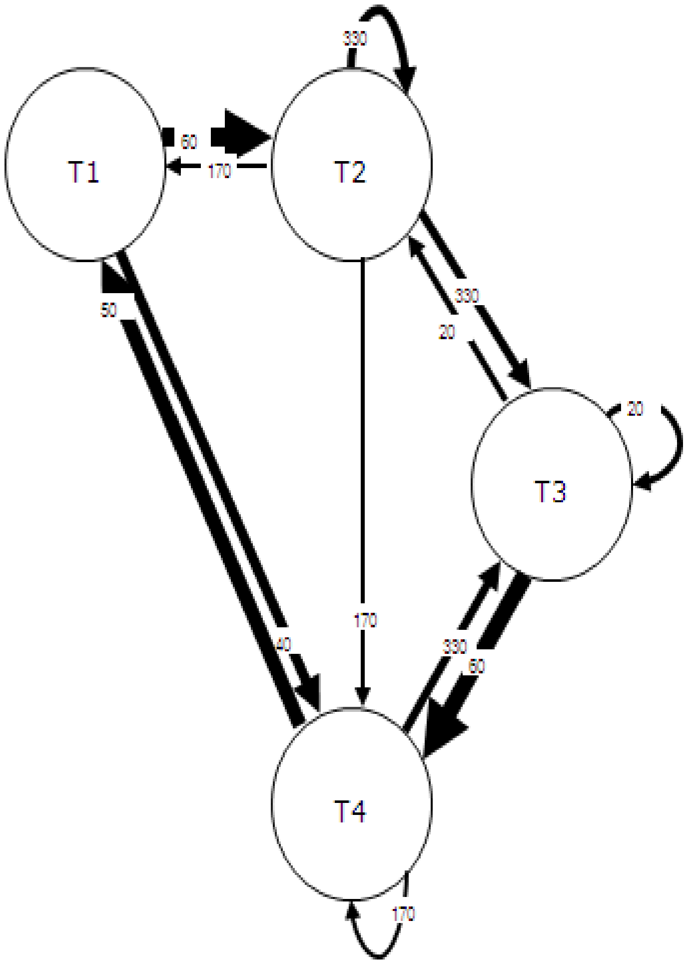


Figure 5.12: Transitional Probabilities Model of 5th Track Dataset

According to the transitional probabilities shown in the fifth model (Figure 5.12), it is able to determine the most possible direction of these four tags. The clearest route in this model is carried out by T1 to T2, T3 to T4, and T4 to T1. Besides, another possible ways to T3 can be seen as either coming from T4 or T2.

The above five models illustrate the transitional probabilities of each tag. At the first glance, it seems that transition between any pair of tags is possible. . However, given the highest value of transitional probabilities of each tag, it is rather possible to locate the direction of these four tags identified in each model. In terms of the individual activity inference, the direction of these four tags can be translated into the creation activity performed by the user. Furthermore, the personal activity in the second experiment was set in a nonlinear movement scenario where the user walked around a table by passing four RFID tags respectively. Therefore, the activity undertaken by the person can be seen as continuous movement undertaken by the user by following the rule of moving from one tag to another tags. To map the transitional direction between these four tags, only the highest transitional probability of each tag was considered to be saved in the model by excluding the possibility that one tag owns highest transitional probability of staying in the same position. Consequently, these five models were reprocessed after determining the criteria. The final probabilities models are modified as follows:

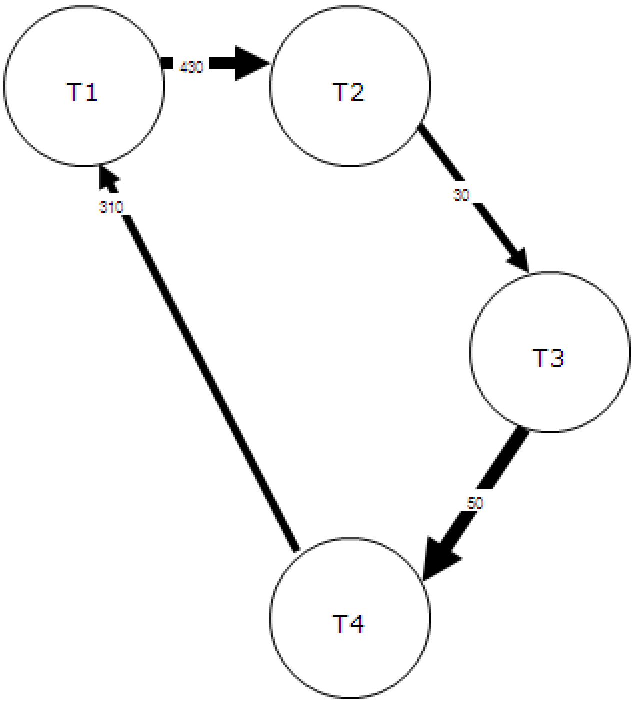


Figure 5.13: Modified Transitional Probabilities Model of 1st Track Dataset

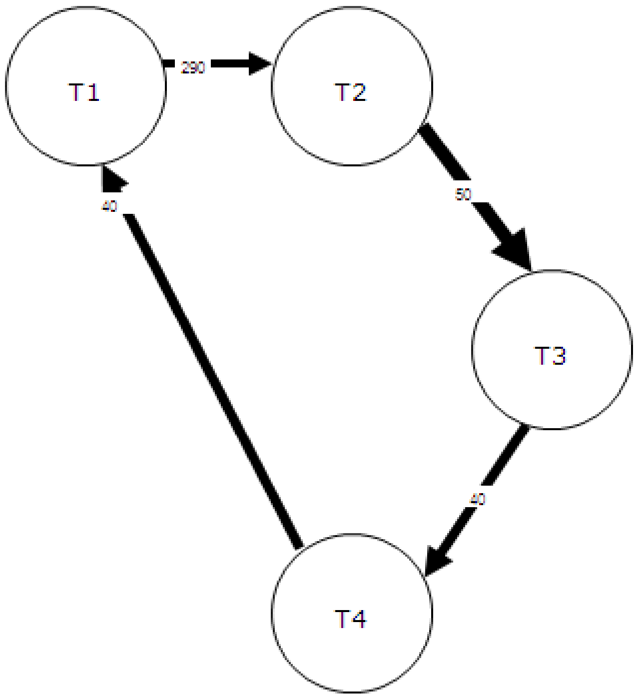


Figure 5.14: Modified Transitional Probabilities Model of 2nd Track Dataset

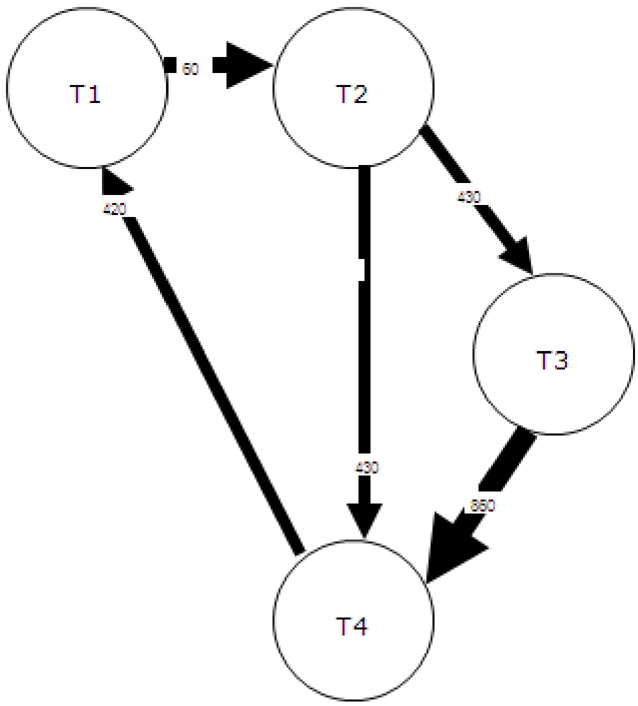


Figure 5.15: Modified Transitional Probabilities Model of 3rd Track Dataset

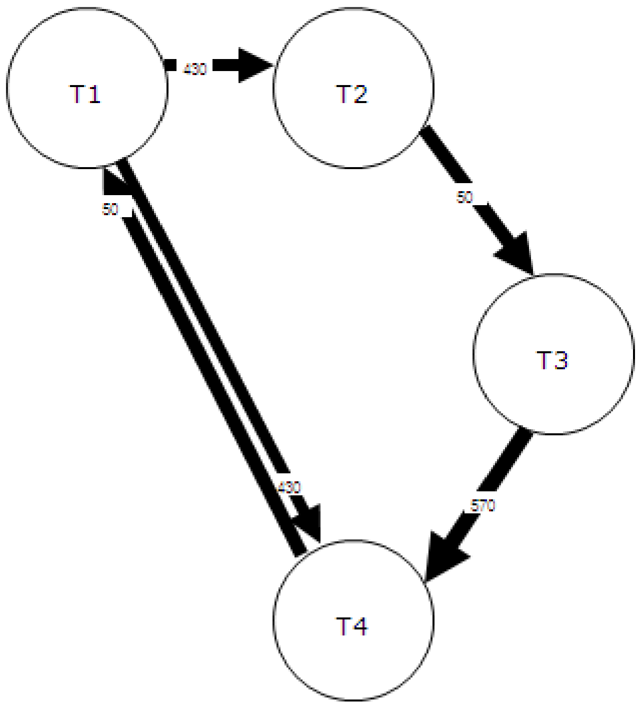


Figure 5.16: Modified Transitional Probabilities Model of 4th Track Dataset

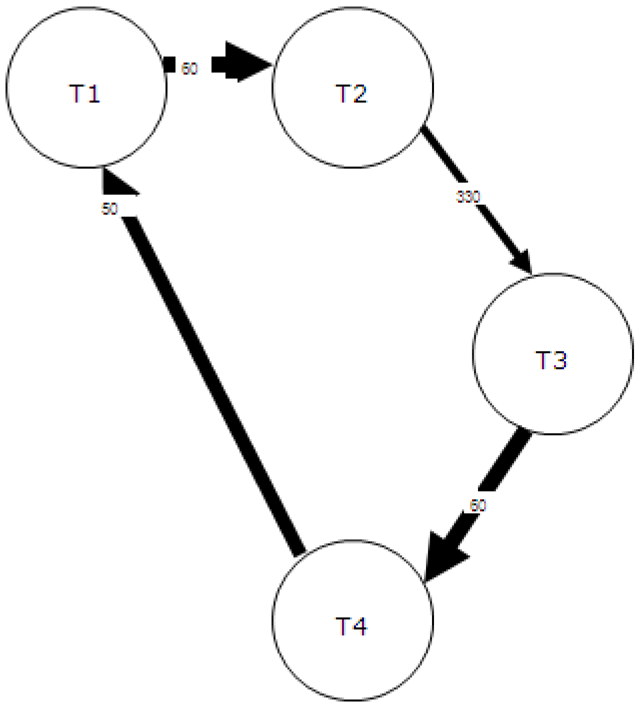


Figure 5.17: Modified Transitional Probabilities Model of 5th Track Dataset

Based on above five polished transitional probabilities models, the most likely transitional direction of each tag is able to be connected. As mention in the second experiment, the start point and end point of activity undertaken by the user were both marked by T1. Thus, the most possible route was mapped from these five models based on the definition of start and end points of the nonlinear movement. In particular, the first, second and fifth model shows three same result of most possible routes, which are all started from T1 to T2, T3, and T4 and ended by T1. However, two different results are exhibited in another two models. By mapping the most possible transitional direction of each tag in these five models, new tag sequences are formatted as follows:

- 1st Model: T1, T2, T3, T4, T1
- 2nd Model: T1, T2, T3, T4, T1
- 3rd Model: T1, T2, T3, T4, T1 or T1, T2, T4, T1
- 4th Model: T1, T2, T3, T4, T1 or T1, T4, T1
- 5th Model: T1, T2, T3, T4, T1

Compared with the standard walking route in the second experiment, it is clear that the first, second and third tracks express the same result to the standard one. Although the third and fourth datasets also provide the same result to the standard one, the possibility of different routes involved in these two data sequences still exists. Due to the personal activity is represented by the walking route where the user passed by, the mistaken information in these models is able to result in the inaccuracy of activity inference. For instance, the third model shows that the user started the activity from T1 to T2, T4 and came back T1 without passing T3. Likewise, it seems the user was even unwilling to pass T2 and T3, but began to walk from T1 to T4 and came back T1 instead. Moreover, these two different routes in the third and fourth models are considered to be the false positive case which degrades the accuracy of detecting personal activity. However, if the information of certain individual motion is specified, the problem of false positive will be able to solved (Kim et al., 2007). In the second experiment, the user was equipped with a RFID reader and walked around a table by passing four tags individually. It assumes that each tag was visited at least once. The tag sequence representing personal walking route in above fives models must contain all four different tags' ID. By applying this rule, two different walking routes displaying in third and fourth models are able to be deleted. The final data sequence generated from each model is presented as follows:

- 1st Model: T1, T2, T3, T4, T1
- 2nd Model: T1, T2, T3, T4, T1
- 3rd Model: T1, T2, T3, T4, T1
- 4th Model: T1, T2, T3, T4, T1
- 5th Model: T1, T2, T3, T4, T1

It is obvious that five models express the same data sequence which is T1, T2, T3, T4, and T1. Compared with the standard data sequence which represents the actual personal activity in the second experiment, there is no difference perceived between these five and the standard one. Every single sequence generated by these five models indicates the same movement which the user demonstrated in the second experiment by passing the four RFID tags in an order of T1, T2, T3, T4, and T1. In this case, it is possible to use the transitional probabilities model for inferring the individual activity.

Chapter 6

Discussion and Future Work

The multi-layer data pre-processing method was proposed in Chapter 5. This chapter discusses several considerable factors that may cause false readings in the RFID data stream as well as comparing two used data clean methods. In addition, the research limitation and future work are also listed in Chapter 6.

6.1 Possible Factors Causing False Readings

This research conducted two different types of personal indoor activities in a laboratory environment. The structure of datasets generated from both experiments differed from each other. However, the noisy data involved in these two different datasets contained the major similarity that all of them were recorded by the reader within a second. As the RFID reader was configured to detect the tag five times per second, it is possible to simultaneously capture the signal from one tag or several nearby tags. Besides, the interference between the RFID devices results in an inaccurate detection. For RFID system with the single reader scenario, the tag collision problem occurs when one reader scans multiple tags at the same time (Carbunar et al., 2008). Additionally, the shorter distance between passive RFID tags, the higher possibility of signal collision occurs in RFID devices (Parry et al., 2007). In these two experiments, the user was equipped with one RFID reader and four RFID tags were placed in a limited area. Thus, the signal reflection between RFID tags is considered to be one of main factors leading to false readings in the RFID reader.

Moreover, the noisy data detected by the RFID reader within one second was categorized as false positive readings according to the definition that tags were recorded outside the detecting region. Another complication is that the user may be within range of two or more tags while moving between them. On the other hand, activity inference is based on the tagged object that the person interacted with. It is found that there was no interaction when the user was in range between these tags. Hence, the personal activity under this circumstance should be represented as being at only one tag at a time.

6.2 Comparison of the Data Pre-processing Methods used

The dataset of first experiment showed either one same tag or two different tags were recorded by the reader several times per second. Since these false positive reads were all shown in one second, an epoch function was carried out by highlighting the noisy data appearing in the same time series. Different tags detected in one second showed that the detected population of one certain tag was larger than the others. In this case, the simple majority voting method was applied in the original data stream as only keeping the majority of tag ID in each epoch. These filtered datasets of the first experiment showed the 100% of similarity to the theoretical tag sequence which represents the correct personal activity. As a result, the original dataset processed by using majority voting method was able to infer personal activity in this research. The accuracy of recognizing individual activity in the first experiment was able to reach 100% by using the majority voting method.

The datasets generated from the second experiment were bigger and more complex than those extracted from the initial experiment. Since the majority voting method effectively filtered datasets of the first experiment, it was then used for removing false readings from the second experiment. Although the noisy data seems to be reduced after employing majority voting method, the pre-processed datasets were still too dirty to be used for inferring the actual personal motion. Therefore, another approach was proposed to eliminate noises escaping from the first level filtering. As the individual activity in the second experiment was a type of continues movement where the user was required to pass four RFID tags respectively, the Markovian transitional probabilities model was adapted to compute the most transitional probability of each tag. Retaining the highest transitional probability at each tag, there were only three out of five models which are able to indicate the same walking direction to the real one while another two models generated two different outcomes. As a consequence, the accuracy of using the Markov Chains Model for inferring the personal motion at this stage was only 60% (3/5).

In the second experiment, however, the user went past four tags in order to complete the nonlinear movement. The rule was added by assuming four tags were visited at least once, which means all four tags ID must be included in the final RFID data sequence. By adding this rule into those transitional probability models, the problematic direction was taken away. Finally, each model presented the accurate walking route where the user walked in the second experiment. In other words, it is able to infer the personal activity by using the Markovian transitional probability model.

The simple method that would be most preferred for the people involved is to firstly take a consideration on dealing with the problems occurred in practice. It is clear that the majority voting method is efficient enough for cleaning the noisy data in the dataset of first experiment. However, the same method is not adequate enough to be used for solving different types of problems. The noisy data appearing in the dataset of second experiment is too stubborn to be removed by using the majority voting method. The standard algorithm of Markov Chains was then utilized in order to get rid of the troublesome noise by keeping the highest transitional probabilities of each data in one sequence. Although there were three models which could directly present the correct nonlinear movement in the second experiment, another two were unable to be used straight for personal activity interference.

Obviously, these two data cleaning methods generate different effects on filtering the raw RFID data stream. Despite the fact that the majority voting method is adequate for cleaning noises in the dataset of linear movement, it is not efficient enough for solving false readings produced by nonlinear movement. Moreover, Markov Chains seem to be a possible approach for inferring the personal activity. But it should be applied in the dataset which was pre-processed by using majority voting method. The combination of majority voting and Markovian transitional probabilities model are able to predict 100% of accuracy after specifying the certain individual movement. What is more is that the starting and ending points prior to the certain activity which is undertaken by the person, needs to be determined before applying this multi level data clean approach.

6.3 Limitations of Research

This research focuses on personal motion inference in an indoor environment by using the relevant the RFID data sequence. There are two types of individual activities that were designed for performing the experiment: linear and nonlinear movement. The placement of RFID tags in these two experiments was different from each other. In the first experiment, four UHF passive RFID tags were linearly and put in order on the surface of a table whereas the same quantity and type of tags were set in each middle line and over the edge of the table. In other words, the personal activity in the initial experiment was performed in one dimension while the person walked along a two dimensional route in the second experiment. The noisy data detected in the datasets of these two experiments varied a lot. In particular, the linear movement appears to contain less number of noisy data points than those detected in the nonlinear movement.

Strictly speaking, the personal activity demonstrated in the first experiment is actually the horizontally linear movement in one dimension. In practice, nonlinear movement can be both vertical and horizontal action. Taking the process of making a cup of tea for example, if the tea bag is put in the cabinet on the wall and the tea cup is on the table, the person who wants to drink the tea needs to take the tea bag from the cabinet and then put it in the cup. Obviously, the activity of making a cup of tea in this case is a kind of linear movement, which can be classified as a vertically action undertaken between two demission. Thus, it is possible that the false reads emerged in the dataset of horizontals linear movement in one dimension may differ from those produced by the other types of linear movement such as vertical linear movement. Although the majority voting method seems to be good enough for removing the false reads from the dataset of the linear movement, it hasn’t been used for cleaning the noisy dataset generated from other types of linear movement. The second experiment presented an indoor personal nonlinear movement where the user walked around a table by passing four

RFID tags respectively and orderly in a clock manner. The walking route in this experiment tends to be in an elliptic shape. In other words, the activity undertaken by the user in the second experiment is considered to be a regular movement. However, the nonlinear movement can be irregular as well. For instance, if the user in the second experiment started activity by returning between two different tags and came back the start point by moving around the third and fourth tags, the walking route would be different from the regular elliptic shape. Hence, the accuracy of applying the Markovian transitional probabilities mode in inferring the irregular nonlinear movement should be concerned.

On the other hand, both methods were used for dealing with the false positive readings in this research. The previous literature indicates that the problem of false negative readings is also obvious in the RFID data stream. The frequency interference or structural barrier influences the readability of the RFID reader, which results in mistaken readings in the RFID data sequence. In this research, one table and four allocated RFID tags were used to be a platform for conducting two experiments in the laboratory environment. No other RFID tags or other physical obstacles were detected near this platform. In the real world practice, however, the human behaviour and the indoor construction structure are more complex than those scenarios defined in the laboratory. The possibility of both false positive and negative reads appearing in a data stream is rather higher in the daily living context. Since both methods were tested in a clean indoor environment, the effect of using these two methods in the more complex environment is considered to be explored.

6.4 Future Work

Future work needs to be carried out based on the limitations of the research. As mentioned before, the same method may not be adequate to cope with all problems. The individual indoor activity in the real world is more complex than those performed in the laboratory environment. The first experiment of this research expresses the personal activity that consists of linear movements. All RFID tags were placed horizontally in one demission, while the second experiment presents a regular nonlinear movement where the user was required to pass by four RFID tags in a predefined route. The primary method applied in solving the noisy data aims at the dataset generated from the predesigned movement. However, the linear movement can be also seen as the vertical or diagonal linear movement. The nonlinear movement can be performed either regularly or irregularly. The accuracy of this multi-level data pre-processing method is expected to have an investigation. Only 4 tags were used for conducting this research and the distance between each tag was similar. It seems to be possible that noise ratio generated from both experiments would increase if more tags were added and placed in different distances. Therefore, one aspect of future research is considered to evaluate the effect of applying current methods in deal with the dataset generated from different circumstances. For instance, a robot that can be programmed to randomly select paths through the RFID network and obtain a rich and voluminous set of data that could be used in more reliable manner for noise removal.

Furthermore, the original Markovian transitional probabilities model can not directly predict 100% of accuracy of activity inference without defining the certain motion undertaken by the user. In this research, the algorithm of Continues-time Markov transitional probability was adopted to filter noisy dataset. In terms of using Markovian Model, however, the Discrete-time Markov Chains would also be considered to apply for getting rid of the noise from original datasets. Thus, finding a more adaptive algorithm or improving current algorithm in an attempt to directly and effectively recognize the personal activity in an indoor environment will be trailed in future work.

Chapter 7

Summary and Conclusion

This research has investigated personal indoor activity inference by using the RFID data sequence. With the fast spread of RFID technology, various applications have been developed and applied in many industries such as manufacturing, retailing and warehousing. All of these applications are related to the area of location identification and object tracking. The recent arisen interest of using RFID technology focuses on monitoring the human motion in an assisted living context. In terms of using RFID system for personal activity inference, the RFID data sequence is a key factor for recognizing the relevant human motion. However, some interference seems easily to appear in RFID equipments, the reliability of using RFID detection can be seen by the end users as a major challenge to its wide implementation. Those unexpected noises producing unreliable data in the final RFID dataset are concluded as a problem of false read. More specifically, there are two major categories of false reads, which are classified as false positive and false negative reads.

The summary of previous chapters is shown as follows:

In Chapter 1, the research objective is introduced as well as two major contributions of this research. Moreover, the research structure is also detailed.

Chapter 2 reviewed a number of literatures regarding to the area of RFID technology and applications. It provides an in-depth view of the development of RFID technology as well as various applications in the different domains. A good understanding of the RFID infrastructure is required for the RFID system design and implementation.

In general, the RFID system is comprised by three typical components, which are the RFID tags, the RFID reader and the host system for extracting and keeping the massive RFID data. There are three RFID frequency ranges that are defined for designing different RFID applications. The lack of global standard is considered to be the obstacle to the growth of the RFID industry. The current standard of RFID system is available from several major vendors.

Due to the attractive features of RFID system such as non line-of-sight, multiple reads high speed, robust, programmability and easy maintenance, the RFID application has been widely applied in many industries. The major RFID applications are concluded as position location, object tracking and activity monitoring. Although there are several other technologies (GPS, ultrasound, Wi-Fi and video camera) that are available for the indoor deployment, the high cost and large infrastructure are the main drawbacks of these technologies. Using the RFID system for sensing individual indoor activity, the information of personal interaction with the tagged object is a crucial factor of the monitoring. Therefore, it is possible to infer the personal activity by analysing the RFID data sequence.

In Chapter 3, a quantitative methodology is presented using design science. As the false reads is the usual phenomenon involved in the RFID sequence, the reliability of using RFID sequence for predicting personal activity needs to be examined. In addition, to gain a realistic and accurate RFID dataset in an indoor environment, the simulation approach is unable to achieve this requirement. Hence, the real experimental measurement seems to be an appropriate approach for collecting the RFID data.

Chapter 4 enfolds the two experiments for personal activity monitoring in a laboratory environment. Two experiments were carried out by using the same RFID system and interacted object. The experiment procedure is shown in section 4.2. However, the experiment result shows the false reads appearing in the raw RFID dataset is the major issue of degrading the accuracy of personal activity inference. In addition, those false reads were all presented as the false positive reads. Thus, it is unable to use the original data sequence to monitor the individual movement.

Chapter 5 analyses the experiment results. As the dataset of both experiments contained obvious false positive reads, the data filtering method was carried out to remove the noisy data from the original dataset. The noisy data and the structure dataset of first experiment were different from the second one. Consequently, a multi level data pre-processing method was carried out to solve these false positive reads. The detailed filtering process and result is also described in this chapter.

In Chapter 6, the comparison of these two methods used in cleaning the original dataset is discussed. However, at the same time, it also points out the limitation of this research. Finally, future work is expected to take a consideration on overcoming the limitation of this research.

In order to examine the degree of those false reads involved in the RFID data sequence impacts on the personal activity inference, two experiments were conducted in this research. The experiment outcome showed the same type of false read (false positive) mixed into the raw RFID data stream, which significantly impacted on the accuracy of individual activity inference. In addition, the less noise was found in the dataset of the first experiment compared with the noisy data in the second one. The structure of original dataset of both experiments differs from each other. To get rid of the false reads from the original RFID dataset, two different data clean methods were carried out in this research, which are majority voting and Markovian transitional probability model. As the first experiment dataset contained less noisy and simple structure, the majority voting was chosen to deal with the noisy data. The filtered dataset showed the perfect accuracy of 100% to the theoretical dataset which represents the exact personal activity in the initial experiment. However, the complexity of noisy data showed in the second experiment was higher than those involved in the primary experiment. The majority voting method was not adequate enough for filtering all datasets of the second experiment. Thus, the standard mathematic algorithm of Markov Chains was employed to present the second level noise filtering. Particularly, several transitional probabilities models were created to map the relation between each variable within the RFID dataset. By keeping the most transitional probabilities, these models only predicted 60% of accuracy. However, adding the condition of specifying the information of interacted objects with personal activity, the accuracy of transition between RFID data to the theoretical RFID detection sequence was able to reach 100%. Thus, these two methods are considered to be an efficient approach for filtering the raw RFID data stream generated from both experiments. In other words, by applying the method of Majority Voting and Markov Transitional Model in filtering raw RFID detection sequence, it is able to predict the exact personal activity undertaken in this research.

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Appendix A: Original RFID Datasets of Linear Movement

Original Tag ID	Original Time Log
E2003411B802011029356367	00:22:02 09/Sep/2008 (GMT)
E2003411B802011029356367	00:22:03 09/Sep/2008 (GMT)
E2003411B802011029356367	00:22:03 09/Sep/2008 (GMT)
E2003411B802011029356367	00:22:04 09/Sep/2008 (GMT)
E2003411B802011029356367	00:22:05 09/Sep/2008 (GMT)
E2003411B802011029356367	00:22:05 09/Sep/2008 (GMT)
E2003411B802011029356356	00:22:06 09/Sep/2008 (GMT)
E2003411B802011029356356	00:22:06 09/Sep/2008 (GMT)
E2003411B802011029356356	00:22:07 09/Sep/2008 (GMT)
E2003411B802011029356356	00:22:08 09/Sep/2008 (GMT)
E2003411B802011029356357	00:22:10 09/Sep/2008 (GMT)
E2003411B802011029356357	00:22:10 09/Sep/2008 (GMT)
E2003411B802011029356357	00:22:11 09/Sep/2008 (GMT)
E2003411B802011029356357	00:22:12 09/Sep/2008 (GMT)
E2003411B802011029356357	00:22:12 09/Sep/2008 (GMT)
E2003411B802011029356368	00:22:15 09/Sep/2008 (GMT)
E2003411B802011029356357	00:22:16 09/Sep/2008 (GMT)
E2003411B802011029356368	00:22:16 09/Sep/2008 (GMT)
E2003411B802011029356368	00:22:16 09/Sep/2008 (GMT)
E2003411B802011029356368	00:22:17 09/Sep/2008 (GMT)

Table A.1: The First Track

Original Tag ID	Original Time Log
E2003411B802011029356356	00:23:52 09/Sep/2008 (GMT)
E2003411B802011029356356	00:23:53 09/Sep/2008 (GMT)
E2003411B802011029356356	00:23:53 09/Sep/2008 (GMT)
E2003411B802011029356356	00:23:55 09/Sep/2008 (GMT)
E2003411B802011029356356	00:24:01 09/Sep/2008 (GMT)
E2003411B802011029356367	00:24:10 09/Sep/2008 (GMT)
E2003411B802011029356367	00:24:10 09/Sep/2008 (GMT)
E2003411B802011029356367	00:24:11 09/Sep/2008 (GMT)
E2003411B802011029356367	00:24:12 09/Sep/2008 (GMT)
E2003411B802011029356356	00:24:15 09/Sep/2008 (GMT)
E2003411B802011029356356	00:24:15 09/Sep/2008 (GMT)
E2003411B802011029356356	00:24:16 09/Sep/2008 (GMT)
E2003411B802011029356356	00:24:17 09/Sep/2008 (GMT)
E2003411B802011029356357	00:24:19 09/Sep/2008 (GMT)
E2003411B802011029356357	00:24:20 09/Sep/2008 (GMT)
E2003411B802011029356357	00:24:20 09/Sep/2008 (GMT)
E2003411B802011029356357	00:24:21 09/Sep/2008 (GMT)
E2003411B802011029356368	00:24:23 09/Sep/2008 (GMT)
E2003411B802011029356368	00:24:24 09/Sep/2008 (GMT)
E2003411B802011029356368	00:24:25 09/Sep/2008 (GMT)

Table A.2: The Second Track

Original Tag ID	Original Time Log
E2003411B802011029356367	00:26:16 09/Sep/2008 (GMT)
E2003411B802011029356367	00:26:17 09/Sep/2008 (GMT)
E2003411B802011029356367	00:26:18 09/Sep/2008 (GMT)
E2003411B802011029356367	00:26:19 09/Sep/2008 (GMT)
E2003411B802011029356367	00:26:19 09/Sep/2008 (GMT)
E2003411B802011029356356	00:26:19 09/Sep/2008 (GMT)
E2003411B802011029356367	00:26:20 09/Sep/2008 (GMT)
E2003411B802011029356367	00:26:21 09/Sep/2008 (GMT)
E2003411B802011029356356	00:26:22 09/Sep/2008 (GMT)
E2003411B802011029356356	00:26:23 09/Sep/2008 (GMT)
E2003411B802011029356356	00:26:23 09/Sep/2008 (GMT)
E2003411B802011029356356	00:26:24 09/Sep/2008 (GMT)
E2003411B802011029356357	00:26:26 09/Sep/2008 (GMT)
E2003411B802011029356357	00:26:27 09/Sep/2008 (GMT)
E2003411B802011029356357	00:26:27 09/Sep/2008 (GMT)
E2003411B802011029356368	00:26:30 09/Sep/2008 (GMT)
E2003411B802011029356368	00:26:31 09/Sep/2008 (GMT)

Table A.3: The Third Track

Original Tag ID	Original Time Log
E2003411B802011029356367	00:27:55 09/Sep/2008 (GMT)
E2003411B802011029356367	00:27:56 09/Sep/2008 (GMT)
E2003411B802011029356367	00:27:57 09/Sep/2008 (GMT)
E2003411B802011029356356	00:27:57 09/Sep/2008 (GMT)
E2003411B802011029356367	00:27:57 09/Sep/2008 (GMT)
E2003411B802011029356356	00:27:59 09/Sep/2008 (GMT)
E2003411B802011029356367	00:27:59 09/Sep/2008 (GMT)
E2003411B802011029356356	00:27:59 09/Sep/2008 (GMT)
E2003411B802011029356356	00:28:01 09/Sep/2008 (GMT)
E2003411B802011029356356	00:28:01 09/Sep/2008 (GMT)
E2003411B802011029356356	00:28:02 09/Sep/2008 (GMT)
E2003411B802011029356356	00:28:03 09/Sep/2008 (GMT)
E2003411B802011029356356	00:28:03 09/Sep/2008 (GMT)
E2003411B802011029356356	00:28:03 09/Sep/2008 (GMT)
E2003411B802011029356357	00:28:05 09/Sep/2008 (GMT)
E2003411B802011029356357	00:28:05 09/Sep/2008 (GMT)
E2003411B802011029356368	00:28:05 09/Sep/2008 (GMT)
E2003411B802011029356357	00:28:06 09/Sep/2008 (GMT)
E2003411B802011029356357	00:28:07 09/Sep/2008 (GMT)
E2003411B802011029356357	00:28:07 09/Sep/2008 (GMT)
E2003411B802011029356368	00:28:09 09/Sep/2008 (GMT)
E2003411B802011029356368	00:28:10 09/Sep/2008 (GMT)
E2003411B802011029356368	00:28:10 09/Sep/2008 (GMT)
E2003411B802011029356368	00:28:11 09/Sep/2008 (GMT)

Table A.4: The Fourth Track

Original Tag ID	Original Time Log
E2003411B802011029356367	00:33:15 09/Sep/2008 (GMT)
E2003411B802011029356367	00:33:16 09/Sep/2008 (GMT)
E2003411B802011029356367	00:33:18 09/Sep/2008 (GMT)
E2003411B802011029356367	00:33:19 09/Sep/2008 (GMT)
E2003411B802011029356367	00:33:19 09/Sep/2008 (GMT)
E2003411B802011029356367	00:33:20 09/Sep/2008 (GMT)
E2003411B802011029356356	00:33:21 09/Sep/2008 (GMT)
E2003411B802011029356367	00:33:22 09/Sep/2008 (GMT)
E2003411B802011029356356	00:33:22 09/Sep/2008 (GMT)
E2003411B802011029356356	00:33:22 09/Sep/2008 (GMT)
E2003411B802011029356356	00:33:23 09/Sep/2008 (GMT)
E2003411B802011029356356	00:33:24 09/Sep/2008 (GMT)
E2003411B802011029356356	00:33:25 09/Sep/2008 (GMT)
E2003411B802011029356357	00:33:26 09/Sep/2008 (GMT)
E2003411B802011029356357	00:33:26 09/Sep/2008 (GMT)
E2003411B802011029356368	00:33:26 09/Sep/2008 (GMT)
E2003411B802011029356357	00:33:27 09/Sep/2008 (GMT)
E2003411B802011029356357	00:33:28 09/Sep/2008 (GMT)
E2003411B802011029356368	00:33:30 09/Sep/2008 (GMT)
E2003411B802011029356368	00:33:31 09/Sep/2008 (GMT)
E2003411B802011029356368	00:33:32 09/Sep/2008 (GMT)
E2003411B802011029356368	00:33:32 09/Sep/2008 (GMT)

Table A.5: The Fifth Track

Appendix B: Customized RFID Datasets of Linear Movement

Time Log	Assigned Tag ID
0:22:02	T9
0:22:03	T9
0:22:03	T9
0:22:04	T9
0:22:05	T9
0:22:05	T9
0:22:06	T6
0:22:06	T6
0:22:07	T6
0:22:08	T6
0:22:10	T8
0:22:10	T8
0:22:11	T8
0:22:12	T8
0:22:12	T8
0:22:15	T5
0:22:16	T8
0:22:16	T5
0:22:16	T5
0:22:17	T5

Table B.1: The First Track

Time Log	Assigned Tag ID
0:24:10	T9
0:24:10	T9
0:24:11	T9
0:24:12	T9
0:24:15	T6
0:24:15	T6
0:24:16	T6
0:24:17	T6
0:24:19	T8
0:24:20	T8
0:24:20	T8
0:24:21	T8
0:24:23	T5
0:24:24	T5
0:24:25	T5

Table B.2: The Second Track

Time Log	Assigned Tag ID
0:26:16	T9
0:26:17	T9
0:26:18	T9
0:26:19	T9
0:26:19	T9
0:26:19	T6
0:26:20	T9
0:26:21	T9
0:26:22	T6
0:26:23	T6
0:26:23	T6
0:26:24	T6
0:26:26	T8
0:26:27	T8
0:26:27	T8
0:26:30	T5
0:26:31	T5

Table B.3: The Third Track

Time Log	Assigned Tag ID
0:27:55	T9
0:27:56	T9
0:27:57	T9
0:27:57	T6
0:27:57	T9
0:27:59	T9
0:27:59	T6
0:27:59	T9
0:28:01	T6
0:28:01	T6
0:28:02	T6
0:28:03	T6
0:28:03	T6
0:28:03	T8
0:28:05	T8
0:28:05	T8
0:28:05	T5
0:28:06	T8
0:28:07	T8
0:28:07	T8
0:28:09	T8
0:28:10	T5
0:28:10	T5
0:28:11	T5

Table B.4: The Fourth Track

Time Log	Assigned Tag ID
0:33:15	T9
0:33:16	T9
0:33:18	T9
0:33:19	T9
0:33:19	T9
0:33:20	T9
0:33:21	T6
0:33:22	T9
0:33:22	T6
0:33:22	T6
0:33:23	T6
0:33:24	T6
0:33:25	T6
0:33:26	T5
0:33:26	T8
0:33:26	T8
0:33:27	T8
0:33:28	T8
0:33:30	T5
0:33:31	T5
0:33:32	T5
0:33:32	T5

Table B.5: The Fifth Track

Appendix C: Original RFID Datasets of Nonlinear Movement

Original Tag ID	Original Time Log
E2003411B802011357286061	09:10:57 21/Sep/2008 (GMT)
E2003411B802011357286060	09:10:57 21/Sep/2008 (GMT)
E2003411B802011357286060	09:10:58 21/Sep/2008 (GMT)
E2003411B802011357286061	09:10:58 21/Sep/2008 (GMT)
E2003411B802011357286061	09:10:58 21/Sep/2008 (GMT)
E2003411B802011357286061	09:10:59 21/Sep/2008 (GMT)
E2003411B802011357286060	09:10:59 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:00 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:00 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:00 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:01 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:02 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:02 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:02 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:02 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:03 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:04 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:04 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:04 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:05 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:06 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:06 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:06 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:07 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:07 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:07 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:07 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:07 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:08 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:08 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:08 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:09 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:09 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:10 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:10 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:11 21/Sep/2008 (GMT)
E2003411B802011357286059	09:11:11 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:11 21/Sep/2008 (GMT)
E2003411B802011357286061	09:11:12 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:13 21/Sep/2008 (GMT)
E2003411B802011357286060	09:11:13 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:13 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:14 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:15 21/Sep/2008 (GMT)

E2003411B802011357286061	09:11:15 21/Sep/2008 (GMT)
E2003411B802011357286061	09:11:16 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:16 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:17 21/Sep/2008 (GMT)
E2003411B802011357286061	09:11:17 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:17 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:18 21/Sep/2008 (GMT)
E2003411B802011357286061	09:11:18 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:19 21/Sep/2008 (GMT)
E2003411B802011357286058	09:11:19 21/Sep/2008 (GMT)
E2003411B802011357286061	09:11:20 21/Sep/2008 (GMT)

Table C.1: The First Track

Original Tag ID	Original Time Log
E2003411B802011357286061	09:20:49 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:49 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:49 21/Sep/2008 (GMT)
E2003411B802011357286061	09:20:50 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:50 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:50 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:51 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:51 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:52 21/Sep/2008 (GMT)
E2003411B802011357286061	09:20:52 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:53 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:53 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:54 21/Sep/2008 (GMT)
E2003411B802011357286059	09:20:55 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:55 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:55 21/Sep/2008 (GMT)
E2003411B802011357286059	09:20:56 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:56 21/Sep/2008 (GMT)
E2003411B802011357286059	09:20:56 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:56 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:57 21/Sep/2008 (GMT)
E2003411B802011357286060	09:20:57 21/Sep/2008 (GMT)
E2003411B802011357286059	09:20:57 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:58 21/Sep/2008 (GMT)
E2003411B802011357286059	09:20:58 21/Sep/2008 (GMT)
E2003411B802011357286058	09:20:59 21/Sep/2008 (GMT)
E2003411B802011357286059	09:20:59 21/Sep/2008 (GMT)
E2003411B802011357286058	09:21:00 21/Sep/2008 (GMT)
E2003411B802011357286059	09:21:00 21/Sep/2008 (GMT)
E2003411B802011357286059	09:21:01 21/Sep/2008 (GMT)
E2003411B802011357286058	09:21:01 21/Sep/2008 (GMT)
E2003411B802011357286061	09:21:01 21/Sep/2008 (GMT)
E2003411B802011357286059	09:21:01 21/Sep/2008 (GMT)
E2003411B802011357286058	09:21:01 21/Sep/2008 (GMT)
E2003411B802011357286061	09:21:02 21/Sep/2008 (GMT)
E2003411B802011357286058	09:21:02 21/Sep/2008 (GMT)
E2003411B802011357286061	09:21:03 21/Sep/2008 (GMT)
E2003411B802011357286058	09:21:03 21/Sep/2008 (GMT)
E2003411B802011357286061	09:21:03 21/Sep/2008 (GMT)
E2003411B802011357286058	09:21:03 21/Sep/2008 (GMT)
E2003411B802011357286061	09:21:04 21/Sep/2008 (GMT)

Table C.2: The Second Track

Original Tag ID	Original Time Log
E2003411B802011357286061	09:22:10 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:10 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:10 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:10 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:11 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:11 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:11 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:12 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:13 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:13 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:14 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:14 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:14 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:15 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:15 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:16 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:16 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:16 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:17 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:17 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:17 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:18 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:18 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:18 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:18 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:19 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:19 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:20 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:20 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:21 21/Sep/2008 (GMT)
E2003411B802011357286060	09:22:21 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:21 21/Sep/2008 (GMT)
E2003411B802011357286059	09:22:21 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:21 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:21 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:22 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:22 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:23 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:23 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:23 21/Sep/2008 (GMT)
E2003411B802011357286058	09:22:23 21/Sep/2008 (GMT)
E2003411B802011357286061	09:22:24 21/Sep/2008 (GMT)

Table C.3: The Third Track

Original Tag ID	Original Time Log
E2003411B802011357286061	09:19:24 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:25 21/Sep/2008 (GMT)
E2003411B802011357286060	09:19:26 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:26 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:26 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:26 21/Sep/2008 (GMT)
E2003411B802011357286060	09:19:26 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:27 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:27 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:28 21/Sep/2008 (GMT)
E2003411B802011357286060	09:19:28 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:28 21/Sep/2008 (GMT)
E2003411B802011357286060	09:19:28 21/Sep/2008 (GMT)
E2003411B802011357286060	09:19:29 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:29 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:30 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:31 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:31 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:31 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:32 21/Sep/2008 (GMT)
E2003411B802011357286059	09:19:32 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:33 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:33 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:34 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:34 21/Sep/2008 (GMT)
E2003411B802011357286058	09:19:35 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:35 21/Sep/2008 (GMT)
E2003411B802011357286061	09:19:36 21/Sep/2008 (GMT)

Table C.4: The Fourth Track

Original Tag ID	Original Time Log
E2003411B802011357286061	09:24:04 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:04 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:05 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:05 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:06 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:06 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:06 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:07 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:07 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:07 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:08 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:08 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:09 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:09 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:09 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:09 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:10 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:10 21/Sep/2008 (GMT)
E2003411B802011357286060	09:24:10 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:11 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:11 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:12 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:12 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:12 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:12 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:13 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:13 21/Sep/2008 (GMT)
E2003411B802011357286059	09:24:14 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:14 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:14 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:14 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:15 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:15 21/Sep/2008 (GMT)
E2003411B802011357286058	09:24:16 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:16 21/Sep/2008 (GMT)
E2003411B802011357286061	09:24:16 21/Sep/2008 (GMT)

Table C.5: The Fifth Track

Appendix D: Customized RFID Datasets of Nonlinear Movement

Time Log	Assigned Tag ID
09:10:57	T1
09:10:57	T2
09:10:58	T2
09:10:58	T1
09:10:58	T1
09:10:59	T1
09:10:59	T2
09:11:00	T2
09:11:00	T3
09:11:00	T2
09:11:01	T2
09:11:02	T3
09:11:02	T2
09:11:02	T3
09:11:02	T2
09:11:03	T2
09:11:04	T4
09:11:04	T2
09:11:04	T2
09:11:05	T3
09:11:06	T4
09:11:06	T2
09:11:06	T3
09:11:07	T3
09:11:07	T2
09:11:07	T4
09:11:07	T4
09:11:07	T2
09:11:08	T3
09:11:08	T3
09:11:08	T4
09:11:09	T4
09:11:09	T3
09:11:10	T3
09:11:10	T4
09:11:11	T4
09:11:11	T3
09:11:11	T4
09:11:12	T1
09:11:13	T2
09:11:13	T2
09:11:13	T4
09:11:14	T4
09:11:15	T4
09:11:15	T1

09:11:16	T1
09:11:16	T4
09:11:17	T4
09:11:17	T1
09:11:17	T4
09:11:18	T4
09:11:18	T1
09:11:19	T4
09:11:19	T4
09:11:20	T1

Table D.1: The First Track

Time Log	Assigned Tag ID
09:19:24	T1
09:19:25	T1
09:19:26	T2
09:19:26	T4
09:19:26	T1
09:19:26	T1
09:19:26	T2
09:19:27	T3
09:19:27	T1
09:19:28	T3
09:19:28	T2
09:19:28	T3
09:19:28	T2
09:19:29	T2
09:19:29	T3
09:19:30	T3
09:19:31	T4
09:19:31	T3
09:19:31	T4
09:19:32	T4
09:19:32	T3
09:19:33	T4
09:19:33	T4
09:19:34	T4
09:19:34	T1
09:19:35	T4
09:19:35	T1
09:19:36	T1

Table D.2: The Second Track

Time Log	Assigned Tag ID
09:20:49	T1
09:20:49	T2
09:20:49	T4
09:20:50	T1
09:20:50	T2
09:20:50	T4
09:20:51	T2
09:20:51	T4
09:20:52	T4
09:20:52	T1
09:20:53	T2
09:20:53	T2
09:20:54	T2
09:20:55	T3
09:20:55	T4
09:20:55	T2
09:20:56	T3
09:20:56	T2
09:20:56	T3
09:20:56	T4
09:20:57	T4
09:20:57	T2
09:20:57	T3
09:20:58	T4
09:20:58	T3
09:20:59	T4
09:20:59	T3
09:21:00	T4
09:21:00	T3
09:21:01	T3
09:21:01	T4
09:21:01	T1
09:21:01	T3
09:21:01	T4
09:21:02	T1
09:21:02	T4
09:21:03	T1
09:21:03	T4
09:21:03	T1
09:21:03	T4
09:21:04	T1

Table D.3: The Third Track

Time Log	Assigned Tag ID
09:22:10	T1
09:22:10	T4
09:22:10	T1
09:22:10	T4
09:22:11	T1
09:22:11	T2
09:22:11	T4
09:22:12	T1
09:22:13	T2
09:22:13	T2
09:22:14	T3
09:22:14	T2
09:22:14	T1
09:22:15	T2
09:22:15	T3
09:22:16	T2
09:22:16	T4
09:22:16	T3
09:22:17	T3
09:22:17	T4
09:22:17	T2
09:22:18	T3
09:22:18	T4
09:22:18	T3
09:22:18	T4
09:22:19	T3
09:22:19	T4
09:22:20	T3
09:22:20	T4
09:22:21	T1
09:22:21	T2
09:22:21	T4
09:22:21	T3
09:22:21	T1
09:22:21	T4
09:22:22	T4
09:22:22	T1
09:22:23	T1
09:22:23	T4
09:22:23	T1
09:22:23	T4
09:22:24	T1

Table D.4: The Fourth Track

Time Log	Assigned Tag ID
09:24:04	T1
09:24:04	T2
09:24:05	T2
09:24:05	T1
09:24:06	T2
09:24:06	T4
09:24:06	T1
09:24:07	T4
09:24:07	T1
09:24:07	T2
09:24:08	T2
09:24:08	T3
09:24:09	T4
09:24:09	T3
09:24:09	T2
09:24:09	T2
09:24:10	T3
09:24:10	T3
09:24:10	T2
09:24:11	T3
09:24:11	T3
09:24:12	T4
09:24:12	T3
09:24:12	T4
09:24:12	T3
09:24:13	T4
09:24:13	T3
09:24:14	T3
09:24:14	T4
09:24:14	T1
09:24:14	T4
09:24:15	T4
09:24:15	T1
09:24:16	T4
09:24:16	T1
09:24:16	T1

Table D.5: The Fifth Track

Appendix E: Linear Movement Datasets Pre-processed by Using Majority Voting Method

Time Log	Assigned Tag ID	Majority voting
0:22:02	T9	T9
0:22:03	T9	T9
0:22:03	T9	
0:22:04	T9	T9
0:22:05	T9	T9
0:22:05	T9	
0:22:06	T6	T6
0:22:06	T6	
0:22:07	T6	T6
0:22:08	T6	T6
0:22:10	T8	T8
0:22:10	T8	
0:22:11	T8	T8
0:22:12	T8	T8
0:22:12	T8	
0:22:15	T5	T5
0:22:16	T8	
0:22:16	T5	T5
0:22:16	T5	
0:22:17	T5	

Table E.1: The First Track

Time Log	Assigned Tag ID	Majority voting
0:24:10	T9	T9
0:24:10	T9	
0:24:11	T9	T9
0:24:12	T9	T9
0:24:15	T6	T6
0:24:15	T6	
0:24:16	T6	T6
0:24:17	T6	T6
0:24:19	T8	T8
0:24:20	T8	T8
0:24:20	T8	
0:24:21	T8	T8
0:24:23	T5	T5
0:24:24	T5	T5
0:24:25	T5	T5

Table E.2: The Second Track

Time Log	Assigned Tag ID	Majority voting
0:26:16	T9	T9
0:26:17	T9	T9
0:26:18	T9	T9
0:26:19	T9	T9
0:26:19	T9	
0:26:19	T6	
0:26:20	T9	T9
0:26:21	T9	T9
0:26:22	T6	T6
0:26:23	T6	T6
0:26:23	T6	
0:26:24	T6	T6
0:26:26	T8	T8
0:26:27	T8	T8
0:26:27	T8	
0:26:30	T5	T5
0:26:31	T5	T5

Table E.3: The Third Track

Time Log	Assigned Tag ID	Majority voting
0:27:55	T9	T9
0:27:56	T9	T9
0:27:57	T9	T9
0:27:57	T6	
0:27:57	T9	
0:27:59	T9	T9
0:27:59	T6	
0:27:59	T9	
0:28:01	T6	T6
0:28:01	T6	
0:28:02	T6	T6
0:28:03	T6	T6
0:28:03	T6	
0:28:03	T8	
0:28:05	T8	T8
0:28:05	T8	
0:28:05	T5	
0:28:06	T8	T8
0:28:07	T8	T8
0:28:07	T8	
0:28:09	T8	T8
0:28:10	T5	T5
0:28:10	T5	
0:28:11	T5	T5

Table E.4: The Fourth Track

Time Log	Assigned Tag ID	Majority voting
0:33:15	T9	T9
0:33:16	T9	T9
0:33:18	T9	T9
0:33:19	T9	T9
0:33:19	T9	
0:33:20	T9	T9
0:33:21	T6	T6
0:33:22	T9	
0:33:22	T6	T6
0:33:22	T6	
0:33:23	T6	T6
0:33:24	T6	T6
0:33:25	T6	T6
0:33:26	T5	
0:33:26	T8	T8
0:33:26	T8	
0:33:27	T8	T8
0:33:28	T8	T8
0:33:30	T5	T5
0:33:31	T5	T5
0:33:32	T5	T5
0:33:32	T5	

Table E.5: The Fifth Track

Appendix F: Nonlinear Movement Datasets Pre-processed by Using Majority Voting Method

Time Log	Assigned Tag ID	Majority Voting
09:10:57	T1	T1
09:10:57	T2	T2
09:10:58	T2	
09:10:58	T1	T1
09:10:58	T1	
09:10:59	T1	T1
09:10:59	T2	T2
09:11:00	T2	T2
09:11:00	T3	
09:11:00	T2	
09:11:01	T2	T2
09:11:02	T3	T3
09:11:02	T2	T2
09:11:02	T3	
09:11:02	T2	
09:11:03	T2	T2
09:11:04	T4	
09:11:04	T2	T2
09:11:04	T2	
09:11:05	T3	T3
09:11:06	T4	T4
09:11:06	T2	T2
09:11:06	T3	T3
09:11:07	T3	
09:11:07	T2	T2
09:11:07	T4	T4
09:11:07	T4	T4
09:11:07	T2	T2
09:11:08	T3	T3
09:11:08	T3	
09:11:08	T4	
09:11:09	T4	T4
09:11:09	T3	T3
09:11:10	T3	T3
09:11:10	T4	T4
09:11:11	T4	T4
09:11:11	T3	
09:11:11	T4	
09:11:12	T1	T1
09:11:13	T2	T2
09:11:13	T2	
09:11:13	T4	
09:11:14	T4	T4
09:11:15	T4	T4
09:11:15	T1	T1

09:11:16	T1	T1
09:11:16	T4	T4
09:11:17	T4	T4
09:11:17	T1	
09:11:17	T4	
09:11:18	T4	T4
09:11:18	T1	T1
09:11:19	T4	T4
09:11:19	T4	
09:11:20	T1	T1

Table F.1: The First Track

Time Log	Assigned Tag ID	Majority Voting
09:19:24	T1	T1
09:19:25	T1	T1
09:19:26	T2	T2
09:19:26	T4	
09:19:26	T1	T1
09:19:26	T1	T1
09:19:26	T2	T2
09:19:27	T3	T3
09:19:27	T1	T1
09:19:28	T3	T3
09:19:28	T2	T2
09:19:28	T3	
09:19:28	T2	
09:19:29	T2	T2
09:19:29	T3	T3
09:19:30	T3	T3
09:19:31	T4	T4
09:19:31	T3	
09:19:31	T4	
09:19:32	T4	T4
09:19:32	T3	T3
09:19:33	T4	T4
09:19:33	T4	
09:19:34	T4	T4
09:19:34	T1	T1
09:19:35	T4	T4
09:19:35	T1	T1
09:19:36	T1	T1

Table F.2: The Second Track

Time Log	Assigned Tag ID	Majority Voting
09:20:49	T1	T1
09:20:49	T2	T2
09:20:49	T4	T4
09:20:50	T1	T1
09:20:50	T2	T2
09:20:50	T4	T4
09:20:51	T2	T2
09:20:51	T4	T4
09:20:52	T4	T4
09:20:52	T1	T1
09:20:53	T2	T2
09:20:53	T2	
09:20:54	T2	T2
09:20:55	T3	T3
09:20:55	T4	T4
09:20:55	T2	T2
09:20:56	T3	T3
09:20:56	T2	
09:20:56	T3	
09:20:56	T4	
09:20:57	T4	T4
09:20:57	T2	T2
09:20:57	T3	T3
09:20:58	T4	T4
09:20:58	T3	T3
09:20:59	T4	T4
09:20:59	T3	T3
09:21:00	T4	T4
09:21:00	T3	T3
09:21:01	T3	T3
09:21:01	T4	T4
09:21:01	T1	
09:21:01	T3	
09:21:01	T4	
09:21:02	T1	T1
09:21:02	T4	T4
09:21:03	T1	T1
09:21:03	T4	T4
09:21:03	T1	
09:21:03	T4	
09:21:04	T1	T1

Table F.3: The Third Track

Time Log	Assigned Tag ID	Majority Voting
09:22:10	T1	T1
09:22:10	T4	T4
09:22:10	T1	
09:22:10	T4	
09:22:11	T1	T1
09:22:11	T2	T2
09:22:11	T4	T4
09:22:12	T1	T1
09:22:13	T2	T2
09:22:13	T2	
09:22:14	T3	T3
09:22:14	T2	T2
09:22:14	T1	T1
09:22:15	T2	T2
09:22:15	T3	T3
09:22:16	T2	T2
09:22:16	T4	T4
09:22:16	T3	T3
09:22:17	T3	T3
09:22:17	T4	T4
09:22:17	T2	T2
09:22:18	T3	T3
09:22:18	T4	T4
09:22:18	T3	
09:22:18	T4	
09:22:19	T3	T3
09:22:19	T4	T4
09:22:20	T3	T3
09:22:20	T4	T4
09:22:21	T1	T1
09:22:21	T2	
09:22:21	T4	T4
09:22:21	T3	
09:22:21	T1	
09:22:21	T4	
09:22:22	T4	T4
09:22:22	T1	T1
09:22:23	T1	T1
09:22:23	T4	T4
09:22:23	T1	
09:22:23	T4	
09:22:24	T1	T1

Table F.4: The Fourth Track

Time Log	Assigned Tag ID	Majority Voting
09:24:04	T1	T1
09:24:04	T2	T2
09:24:05	T2	T2
09:24:05	T1	T1
09:24:06	T2	T2
09:24:06	T4	T4
09:24:06	T1	T1
09:24:07	T4	T4
09:24:07	T1	T1
09:24:07	T2	T2
09:24:08	T2	T2
09:24:08	T3	T3
09:24:09	T4	
09:24:09	T3	
09:24:09	T2	T2
09:24:09	T2	
09:24:10	T3	T3
09:24:10	T3	
09:24:10	T2	
09:24:11	T3	T3
09:24:11	T3	
09:24:12	T4	T4
09:24:12	T3	T3
09:24:12	T4	
09:24:12	T3	
09:24:13	T4	T4
09:24:13	T3	T3
09:24:14	T3	
09:24:14	T4	T4
09:24:14	T1	
09:24:14	T4	
09:24:15	T4	T4
09:24:15	T1	T1
09:24:16	T4	
09:24:16	T1	T1
09:24:16	T1	

Table F.5: The Fifth Track