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Tracking Spatio-temporal Movement of Human in Terms of Space Utilization Using Media-Access-Control Address Data

ABSTRACT

Using Media-Access-Control (MAC) address for data collection and tracking is a capable and cost effective approach as the traditional ways such as surveys and video surveillance have numerous drawbacks and limitations. Positioning cell-phones by Global System for Mobile communication was considered an attack on people's privacy. MAC addresses just keep a unique log of a WiFi or Bluetooth enabled device for connecting to another device that has not potential privacy infringements. This paper presents the use of MAC address data collection approach for analysis of spatio-temporal dynamics of human in terms of shared space utilization. This paper firstly discuses the critical challenges and key benefits of MAC address data as a tracking technology for monitoring human movement. Here, proximity-based MAC address tracking is postulated as an effective methodology for analysing the complex spatio-temporal dynamics of human movements at shared zones such as lounge and office areas. A case study of university staff lounge area is described in detail and results indicates a significant added value of the methodology for human movement tracking. By analysis of MAC address data in the study area, clear statistics such as staff's utilisation frequency, utilisation peak periods, and staff time spent is obtained. The analyses also reveal staff's socialising profiles in terms of group and solo gathering. The paper is concluded with a discussion on why MAC address tracking offers significant advantages for tracking human behaviour in terms of shared space utilisation with respect to other and more prominent technologies, and outlines some of its remaining deficiencies.

Keyword: Crowd Data, MAC Address, Space Utilisation, Human Movement Tracking

1. INTRODUCTION

Extraction features from spatio-temporal movement of human has become an interesting topic in terms of crowd congestion control, safety, public transport and human behaviour assessment. The robust passive and active positioning technologies have motivated the development of sensors which have the capability of human movement monitoring. Human movement behaviour analysis has received attention particularly in the field of visual analytics (Andrienko and Andrienko, 2007a, Andrienko et al., 2007). The demonstration and analysis of big volumes of trajectory data of objects moving through geographical space has recently become a major topic of interest in research areas such as computer science (Bogorny et al., 2009, Orlando et al., 2007), geographical information science (Ahlqvist et al., 2010, Shaw et al., 2008), urbanism (Van Schaick and Van der Spek, 2008) and visual analytics(Andrienko and Andrienko, 2007b). The movements analysis of various kinds of objects including vehicles (Quiroga and Bullock, 1998), animals (Laube et al., 2007), bank notes (Brockmann et al., 2006) and typhoons (Terry and Feng, 2010) have been focused in recent studies. However, the greater part of research has been applied to people movement in different contexts and at various scales, the movement of athletes on a pitch (Laube et al., 2005), tourists on a regional (Ahas et al., 2008) and local scale (Kemperman et al., 2009, O'Connor et al., 2005, Shoval and Isaacson, 2007), and customers in a supermarket (Hui et al., 2009) for example. Advanced tracking knowledge complements more traditional qualitative methods in these contexts, such as shadowing (Quinlan, 2008) and collecting travel diaries (Axhausen et al., 2002).

Surveys and video surveillance are the most common methods for customers and people data acquisition. However, high cost and also hardly representing of surveys because of a non-random sampling process are always a problem. Video processing is also depended on weather conditions, illumination changes, limited viewing angles, density and brightness of crowd (Liebig and Wagoum, 2012). Having difficulty to unambiguously distinguish between people in a crowd because of dense packing and constant interactions among individuals is another major shortcoming of video-based human data collection. The complexity of this method also increases with respect to the reconstruction of individual movements across multiple camera angles. Therefore, current applications of video data collection have achieved to capture the spatio-temporal paths of only limited objects in few spatial environments (Dee and Velastin, 2008), severely restricting its use as a tracking method in the context of human behaviour evaluation in space utilisation.

Increasing the popularity of cell phones has motivated researchers to collect crowd data based on recording people's mobile phones. Positioning the cell-phones based on Global System for Mobile (GSM) communication was proposed as a popular and accurate method but it has become less applicable most importantly due to the privacy objection (Giannotti and Pedreschi, 2008). In response to these issues and given the ubiquity of Bluetooth-enabled devices such as smart phones and tablets carried around by their owners, WiFi and Bluetooth technologies have increasingly been suggested as a simple and low-cost alternative for the reconstruction of spatial behaviour (Bullock et al., 2010, Wasson et al., 2008, Versichele et al., 2010, Mottram, 2007, Van LonderseLe et al., 2009, Leitinger et al., 2010). Also, tracking individual in this method remains unknown avoiding potential privacy infringements because each fixed Media Access Control (MAC) address cannot be associated to any personal information such as names or mobile numbers. Bluetooth and WiFi based monitoring data is also increasingly being used for road traffic monitoring and management (Bhaskar et al., 2014, Tsubota et al., 2014, Tsubota et al., 2011, Khoei et al., 2013, Kieu et al., 2012).

Because MAC address data allows for unannounced, non-participatory, and simultaneous tracking of people, it is especially useful to study the evaluation of human behaviour in terms of utilisation of space based on devices located in the space. MAC address is useful only when measuring positions of individuals who are using devices. This paper aims to significantly augment the current knowledge by reporting on a recent and comprehensive experiment using MAC address data as a tracking technology. The experiment was carried out at one of the staff office lounges of Queensland University of Technology in Brisbane, Australia. This setting offers a challenging analysis in terms of human behaviour evaluation in shared space utilisation including evaluation of lounge area utilisation frequency, daily time spending, utilisation peak periods, and group or solo utilisation. The goal of this case study was to explore the potential of MAC address tracking for studying the spatio-temporal dynamics of human in space utilization by highlighting a selection of analytical possibilities with the gathered data and showing the corresponding results. The outcomes of this data can be used for studying human behaviour in response to space design, change and utilisation. The results of data analysis can be also used to significantly enhance the performance of facility management team in terms coordinating their staff, providing satisfactory quality service and facilities. It results in balancing investment costs and quality service by optimal facility procurement and staff management.

The rest of the paper is organised as follows. Section 2 presents a brief discussion of MAC address data as a tracking technology. Section 3 describes the experimental design of the case study, and Section 4 describes the results of this study. The results have been finally contextualized, argued why MAC address data has the potential to become a valuable methodology for studying the dynamics associated with human behaviour in space utilisation, and outlined some of its remaining deficiencies in Section 5.

2. MAC ADDRESS DATA AS A TRACKING TECHNOLOGY

2.1. Working Principle

In order to access networks and services with higher flexibility and mobility, wireless networks are a popular and fast-growing technology (Hossain and Wee-Seng, 2007). The benefits of wireless are reducing the cable restrictions, low cost, dynamic communication formation, and easy deployment. Bluetooth, WiFi, ZigBee, and UWB are four short range wireless standards that respectively correspond IEEE 802.15.1, 802.11 a/b/g, 802.15.4, and 802.15.3. In fact, IEEE defines the MAC address and Physical Layers for mentioned wireless protocols for an operation range of 10 to 100 meters. Bluetooth and ZigBee are most efficient in terms of power consumption and UWB and WiFi consume less normalized energy. Furthermore, ZigBee and Bluetooth have bigger transmission time and data coding efficiency associated to the data payload size (Porter et al., 2012). Nowadays, majority of smart-phones and digital devices use Bluetooth and WiFi technologies for communication.

MAC addresses are indeed unique identifies and are used for various type of communication networks and most of IEEE 802 network technologies. Hence, they can be tracked and this feature has been a motivation for various applications and data collection. Several factors may affect on the quality of MAC address data collection process that may be associated with the hardware and software implemented (Bhaskar and Chung, 2013). Antenna characteristic is one of those factors. Porter et al., categorised six different antennas for assessing their capability and suitability in the Bluetooth data collection process. They evaluated the antennas' performance for Bluetooth traffic data collection. Their study shows that vertically polarized antennas with gains from 9 to 12 dBi are suitable for a Bluetooth based traffic data collection. They also mentioned that the circular polarized antennas do not significantly improve the data collection process (Porter et al., 2012). MAC address discovery time is also important in terms of collecting efficient data during a time period. Bluetooth discovery time is theatrically 10.21 seconds (Han and Srinivasan, 2012) whereas WiFi discovery time is around 1 second (Chakraborty et al., 2010).

Radio-Frequency Identification (RFID) is a wireless technology for identification of objects. Similar to MAC address, each RFID tag contains unique numbers which can be read wirelessly. In terms of collecting data from people's spatio-temporal movement, MAC address has some benefits compared to RFID. People may not tend to carry a RFID tag as they may concern about their privacy, whereas MAC address remains anonymous. Asking people to carry a RFID tags will also require explaining them about tracking their behaviour. People may change their behaviour when they are aware of a data collection and tracking system. This awareness can impact on people's behaviour and change their regular habits. In case of scanning MAC addresses, it's not necessary to let people know about sampling their movement.

The interference of environment's obstacle on the wireless communication is another significant issue that highly impacts on MAC address detection range. Some factors that cause considerable interference are (Harwood, 2009):

- Physical objects (such as Trees, masonry, buildings, and other physical structures)
- Radio Frequency (RF) interference (such as microwave and cordless phones)
- Electronics Device interference (computers, refrigerators, fans and lighting fixtures)
- Environmental factors (such as weather conditions, fog, and lighting)

While outdoor interference such as weather condition is not a serious problem, there are plenty of wireless obstacles in indoor spaces such as offices and homes. Table 1 presented the obstacle severity on wireless communication.

Table 1

2.2. Related Works

Collection data from capturing wireless technologies such as Bluetooth and WiFi which communicate based on MAC address standards have been recently applied successfully. Nowadays, majority of smart phones, laptops, and portable electronics devices use wireless communication, especially Bluetooth and Wi-Fi. The presence of Bluetooth and WiFi networks in offices, buildings and campuses (Bisdikian, 2001, Bray and Sturman, 2001) have been increased because of their wide availability on a huge number of personal portable electronic devices. Bluetooth tracking technology has been applied for the estimation of travel times and prediction (Haghani et al., 2010, Wasson et al., 2008) public transport utilisation in Graz (Weinzerl and Hagemann, 2007) and movement behaviour assessment in shopping centres (Millonig and Gartner, 2008).

With increasing the popularity of using mobile devices, new techniques have been presented for analysis of massive distributed movement data (Jankowski et al., 2010, Andrienko and Andrienko, 2007a). Tracking mobile phones and intercoms have been recently noticed as an effective crowd data collection and monitoring system (Liebig and Wagoum, 2012, Stange et al., 2011). Recent studies have been done on the analysis of people's travelling behaviour in the tourism industry (Jankowski et al., 2010) and pedestrian's density distribution during seasons (Andrienko et al., 2009) for example.

Bluetooth technology has recently become an emerging tool for monitoring purposes (Stange et al., 2011). Some studies have been done on recording flows of outdoor movements using Bluetooth. Versichele et al., studied the potential and implication of Bluetooth proximity-based tracking in moving objects (Versichele et al., 2010). Leitinger et al., developed a Bluetooth-based mobility sensor for event monitoring at Szinger festival in Budapest (Leitinger et al., 2010). They placed a mesh of six sensors at selected locations with distance from 50 to 200 meters. Their work extracted the number of people with their route choice at specific locations. Pels et al., implemented various scanners at Dutch train stations for capturing transit travellers (Pels et al., 2005). Weinzerl and Hagemann analysed the transit travellers and also tracked public busses by locating sensors inside the buses (Weinzerl and Hagemann, 2007). Versichele et al., used Bluetooth data as a tracking technology for analysis spatio-temporal movement of festival visitors (Versichele et al., 2012b). Versichele et al., also presented an intelligent event management with Bluetooth sensor network (Versichele et al., 2012a). Abedi et al., compared the popularity of WiFi and Bluetooth in terms of human movement data collection. Their study showed that WiFi is more popular and has higher scanning rate compared to Bluetooth devices (Abedi et al., 2013). Stange et al., also used Bluetooth tracking system for monitoring visitors with extracting their pathway choice (Stange et al., 2011). Delafontaine et al., Analysed spatio-temporal sequences in Bluetooth tracking data to examine the behaviour patterns of visitors at a major trade fair in Belgium (Delafontaine et al., 2012). Vu et al., presented a joint Bluetooth/WiFi scanning framework for assessment of the location popularity and people time spending in a university campus area (Vu et al., 2010).

3. EXPERIMENTAL DESIGN

3.1. Equipment

Fig. 1 shows the hardware components used for data collection in this experiment. For capturing MAC addresses, a WiFi/ Bluetooth scanner called *CrossCompass* manufactured by *Acyclica Inc* with the capability of scanning Bluetooth and WiFi addresses separately and simultaneously. This device can also be synchronised with GPS or PC clock. Based on experimental results, this scanner can scan WiFi devices up to 15 meters and Bluetooth devices up to 10 meters without using any external antenna. It's WiFi and Bluetooth discovery times are experimentally computed from over 10,000 records. This device discovers WiFi addresses every 1.37 seconds in average and Bluetooth IDs in almost 5.57 seconds. Because its minimum detection range and average discovery time are appropriate and suitable for the case study, this scanner was selected for data collection.

Fig. 1

3.2. Description of Study Area

The area proposed for case study is one of the staff lounges of Queensland University of Technology (QUT) in Brisbane, Australia. It is actually located in the seventh floor of S block in QUT Gardens Point campus. Around 50 people including university lectures, academic research fellows and research students are allocated to this floor. Also, there is not any lecture room in this floor and it is only allocated to research students and staff. Other research staff from level 6 and 8 may come to this floor as it is fashion designed and widely equipped. As can be seen from Fig. 2, this area includes kitchen, dining tables and resting sofas. The MAC address scanner was located into one of kitchen cabinets shown by "MAC" sign in the spatial map in Fig. 2.

This area was selected for experimental implementation because various groups of research and academic staff utilise this area for dining and spend their leisure times. Also, group gathering for dining or drinking has been observed many times in this space. As a result, it was proposed as a place that socializing behaviour profile of human can be also detected, tracked and analysed. Except staff, other people including undergraduate student and ordinary people as a visitor may come to this area. In addition, this space provides free wireless network for QUT staff, students and some visitors. This free facility increases the likelihood of scanning more WiFi devices as people tend to surf internet through a free WiFi rather than cellular internet. Cell-phones are the main target because people tend to carry them in their pocket most of times. Tablets and laptops are other devices that may be carrying by participants in the experiment area.

Fig. 2

3.3. Pre-Processing

The raw data consisted of log files on the implemented scanner has the following format: timestamp of detection, MAC address of the detected devices and signal strength. Fig. 3 shows an extract of logged data. After merging the log files of three weeks, the dataset consisted of 35,873 loglines and 418 unique devices. In order to obtain a compressed dataset, unique addresses which were scanned only once daily or observed once a week have been removed. Also, the MAC addresses that their interval between the first and last observations was less than 4 minutes during a period of 1 hour have been considered as passing visitors and filtered. Different scenarios such as picking and dropping food in the fridge were done in order to estimate minimum time period that can be counted as utilisation period. These criteria were decided by statistical approach. Results of these experiments showed that over 3 minutes must be considered for area utilisation period. Furthermore, all records overnight periods were not considered as useful data for analysis. The devices which were scanned for long hours or entire business hours were counted as noise and removed. In this way, the dataset was compressed to 34,622 loglines and 239 unique devices.

Fig. 3

Fig. 4 shows the distribution of collected data before and after pre-processing stage. Fig. 4*a* has distribution from all the observations, whereas Fig. 4*b* is from the unique records. The graphs indicate that there is not a significant drop in the number of records (*see* Fig. 4*a*) while the number of unique devices was compressed to almost 30% (see Fig. 4*b*). The pre-processing stage thus filtered ineffectual records and unique IDs. Fig. 5 illustrates the distribution of detected unique WiFi address during for three consecutive weeks over time after pre-processing. Here the unique records for each time period are cumulated for the three weeks. Lower, middle and upper band in Figure 5 represents records for Week 1, Week 2 and Week 3, respectively. As expected, the highest proportions of unique observations are from 10 AM to 6 PM during all three weeks.

Fig. 4

Fig. 5

4. RESULTS AND DATA ANALYSIS

4. 1. Frequency of Utilisation

This section presents the behaviour of staff in terms of utilising the lounge area during all three weeks. Fig. 6 illustrates the radar plot for common devices for each week where the number of unique records of a particular week day and the number of these records observed in other week days are presented. For instance, red line with square represents unique records observed on Tuesday. Here for Week-1 (first plot in Fig. 6) we have observed 40 unique MAC records on Tuesday. Out of this 40 unique ID we have observed 10, 10, 15 and 10 records on Monday, Wednesday, Thursday and Friday, respectively. From Fig. 6 it can be concluded that between 8 to 10 staff utilise the area on all week days in each week, because there is no observation less than 8. The pattern of all three weeks is similar, with peak on Thursdays. This indicates that people who mostly use the area repeat similar weekly habits in terms of space utilisation.

The distribution of staff attendance of the area along each week is presented in Fig. 7. Here, blue bar, light brown, and dark brown represents percentage of regular visitors for all the 5 days, 4 days and less than 3 days, respectively. It is observed that the over 50% of visitors utilise the area for 4 business days a week. Only 10% -15% of visitors are regular users for all the 5 days.

Fig. 8 focuses on the distribution of common unique devices captured within different time period of the day and for different days of the weeks. Here each radar plot is for a specific day of the week. It is observed that:

a) Tuesday, Wednesday and Thursday have three peaks at 9:00-11:30 AM; 11:30 AM-2:30 PM; 2:30-5:30 PM, indicating the time when most of the people utilising the area.
b) Monday has only two peaks during 11:30 AM-2:30 PM and 2:30-5:30 PM and. This indicates that most of the people come to the area during lunch (11:30-2:30 PM) and afternoon tea (2:30-5:30 pm) but not much during morning (9:00-11:30 AM).
c) Friday, the distribution is scattered and its pattern is different from other days of the weeks.

This indicates that the utilisation of the space over different time of the day and day of the week is different with Monday and Friday having different patterns than the other working days. Though, majority of detected staff utilised the shared area during lunch period (11:30-2:30 PM) for all the working days.

Fig. 9 demonstrates the proportion of staff utilisation frequency over three weeks. Here X-axis (*number of visits*) is the number of time periods a person is observed during the week and Y-axis is the percentage of such observations. The day is divided into 5 time periods (*Early Morning* (6:30 to 9), *Morning* (9 to 11:30), *Lunch Time* (11:30 to 14:30), *Afternoon* (14:30 to 17:30) and *Dinner Time* (17:30 to 20), *Refer to* Fig 8). Let's take an example to explain the graph. Say, a person is observed during two time periods (11:30 AM-2:30 PM and 5:30 PM- 8:00PM) on Friday in Week-1 then this observation will be considered as *twice* visits in Week-1. If the same person is observed on another day for only a time period then this observation will also be considered as *once* visit in the respective week. Analysing the graph in Fig. 9 we can conclude that: a) The majority of the staff utilised the area *twice* a day in all three weeks; and b) Less than 3% used the lounge only one period per day. Hence the lounge is utilised by a person for multiple times a day.

Fig. 6

Fig. 7

Fig. 8

Fig. 9

4.2. Time Spending

This section presents the time spent by people in the lounge area during different periods of a day, where a day is categorised into five periods as discussed above. Fig. 11 represents Box plots of the time spent (utilisation of the lounge) during week days for different time periods. Each sub plot is for different day of the week. Here, for each visit of the person, only the time spend more than 3 minutes is considered. To count valid log records, the only unique devices were considered that have being continuously observed during each day periods for at least 3 minutes. For example, if a device was observed once around 9:30 AM and once in 10:30 AM, this device was not extracted as time spending feature for *Morning* period. Fig. 10 shows an example of which type of records was counted for time spending analysis. In this example, ID#2 was on observed in two periods during morning time. Both periods are less than 3 minutes and were not counted as a valid time spending data. Time periods spent by ID#1 and ID#5 are counted as valid data. The first period of ID#4 is invalid and the second period is accepted for analysis. In case of ID#3, just the time period after 9:30 AM is considered as morning time spent data.

It can be concluded from Fig. 11 that people tend to spend more time during lunch periods of working day. Early morning and evening have lower amount of utilisation time. Mornings and afternoons were second popular period for staff to utilise the lounge area. In overall, the pattern of utilisation time between weekdays was almost same. These results explain that people utilise the lounge space mostly for their lunch.

Fig. 10

Fig. 11

4.3. Group Gathering and Socializing

During our analysis on the data of three consecutive weeks, some groups were found that they spend time *together* regularly. Here, devices which regularly entered and exited the lounge area in almost similar time (within 3 minutes) during lunch periods for all the observations were considered as a *group*. Devices which were not entered or exited the lounge with other device in almost similar time (within 3 minutes) were considered as *individual*. The devices which are neither *individual* nor *group* are considered as *unknown*. For instance, say devices A, B and C have entered and exited the lounge for all the days expect one. On the exceptional day A and B have entered and exited together, then A and B are *grouped* where as C is *unknown*. Fig. 12*a* illustrates pie charts for proportion of the devices that utilise the lounge area. It is observed that only 12% of the devices are *group* and over 67% are *individual*.

Fig. 12*b* illustrates pie chart for the regular attendees. Here, only the devices which are observed during the lunch for at least three times a week (more than 50% of the week) are considered as regular attendees. It is observed that the *grouped* devices have the highest proportion of the regular attendance. It is over 52% here. This indicates that although group devices are only 12% of the visitors, but they utilise the lounge more often than *individuals*. This is further backed by the analysis between the time spending during lunch period by *individual* and *group* (see Fig 13). The median of the time spend by *group* (approx 40 minutes) is higher than that of the *individual* (approx 20 minutes).

Fig. 12

Fig. 13

5. DISCUSSION AND CONCLUSION

This paper presents the use of MAC address data as an effective tool for tracking and analysis of the spatio-temporal dynamic of human in terms of shared space utilisation behaviour. The analysis of three-week data showed that it is possible to analyse the human behaviour in different aspects with this data collection technology in terms of space utilisation. This analysis could estimate staff utilisation spent time and frequency during a day and week. This method identified and tracked the people who regularly utilise the lounge area with lower setup and processing costs. Also, this method could identify and track group gathering and extract their behaviour pattern.

5.1. The Added Value of MAC Address Tracking

The outcomes of this study proved the functionality and significance of MAC data for human behaviour analysis. The results of this paper extracted some human behaviour features that are difficult and expensive through other methods such as camera and survey. In the independent data collection mode, this tracking method could effectively extract valuable human behaviour information such as frequency of utilisation, utilisation time, group utilisation and socialising. However, the method accuracy is dependent on how many devices are turned on during the data collection.

The outcomes of this study can be applied for various purposes. By identifying the peak periods of utilisation, the facility management team can optimise their performance by selecting critical periods for inspection and providing facilities. Also, this team can be aware of people's response to space design change or new facility setup such as upgraded coffee machine, adding a TV and entertainment facilities. This kind of knowledge from people's behaviour can facilitate them for the implementation of future plans with minimum risks. In another aspect, the results will be useful for human resource management team to understand the social behaviour of people. This knowledge will guide them to setup plans for enhancement of their social activities such as organising weekly or monthly social events.

5.1. Suggestions for Future Research

MAC address tracking technology can extract more valuable human behaviour information. This study was a successful model that investigated human behaviour in a little society. This model can be extended to larger spaces and various scenarios in order to collect data and analysis human behaviour in response to environmental and society structure. In another word, it is possible to assess spatio-temporal dynamics and behaviour of human for following goals based on MAC data:

(1) **Human socialising behaviour assessment.** The behaviour of individuals can be assessed in terms of socialising from when they relocate in a new place until they join a group for social activities. This period can be called *First Socializing Interval*. Also, the effectiveness of various social events can be evaluated in terms of decreasing *First Socializing Interval* duration.

(2) **Human social behaviour assessment.** In this case, individuals behaviour in a group society can be assessed and categorised into some divisions such as

- **Loyal:** people who are loyal to a group and spent most of their time with them
- **Outlier:** people who leave a group and join to another group
- **Flier:** people who spend their time with different groups
- **Solo:** people who does not socialised

(3) **Human response to changes of environmental structure.** Collecting MAC data during a design or structural change of a shared environment such as a workplace can demonstrate the response of people to the changes. This change can be adding or removing a facility from a workplace for example.

The outlined human information can be acquired by MAC tracking technology that other human tracking technologies are not able to extract and study these information. As a future direction for enhancement of monitoring human movement, complementing of MAC data with camera and other tools can remarkably develop human behaviour information collection part and deliver new and abstruse features of human behaviour.

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Fig. 1. WiFi and Bluetooth MAC address scanning hardware used for data collection: computational unit (1), WiFi (2) and Bluetooth (3) antenna connector, USB storage (4), 3 dBi omni-directional antenna (5), LAN cable (6) for data connection to PC, 240v AC to 5v DC power convertor (6) and rechargeable 14v acid batter.

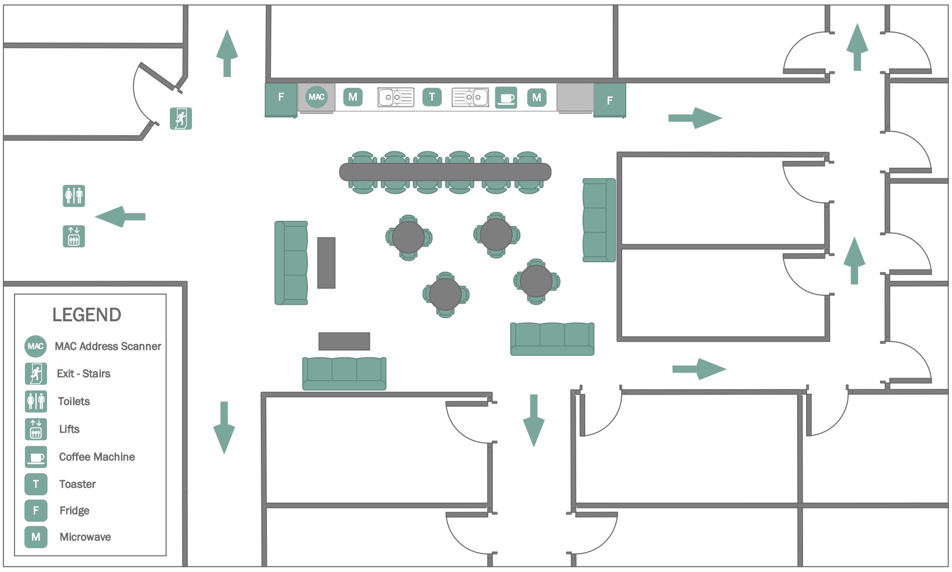


Fig. 2. Picture (up) and spatial map (down) of study area

1373033902	38:e7:d8:02:9c:c7	-76
1373033904	38:e7:d8:02:9c:c7	-76
1373033904	f8:db:7f:7c:5c:3e	-75
1373033906	f8:db:7f:7c:5c:3e	-74
1373033906	3c:5a:37:0a:20:4f	-77
1373033909	3c:5a:37:0a:20:4f	-71

Fig. 3. Extract of logged data demonstrating the raw time detection data on Friday 5th July 2013 between 14:18:22 to 14:18:29. The first column represents date and time in UTC format. A WiFi MAC address (f8:db:7f:7c:5c:3e), for example, being detected twice from 14:18:24 (1373033904) and 14:18:26 (1373033906) on Friday 5th July 2013. The third column indicates detected signal strength.

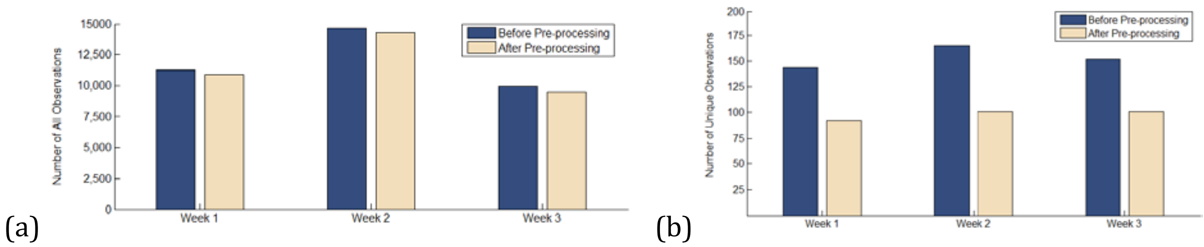


Fig. 4. Distribution of data before and after pre-processing stage: a) All MAC observation; b) Unique MAC observations

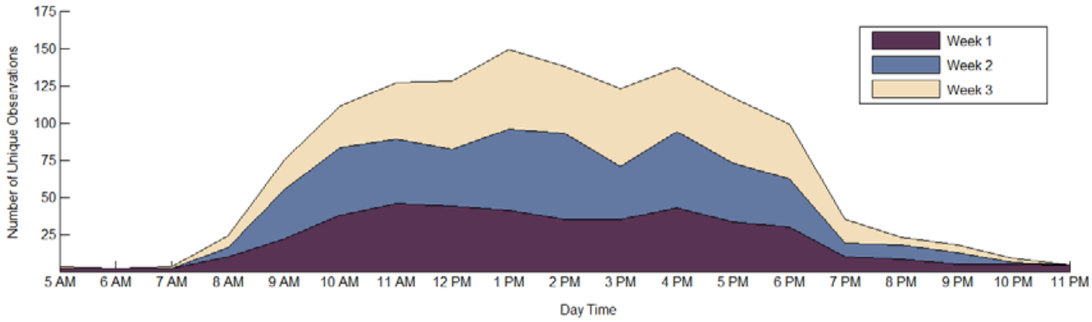


Fig. 5. Distribution of the detected WiFi address during for three consecutive weeks over time after pre-processing phase

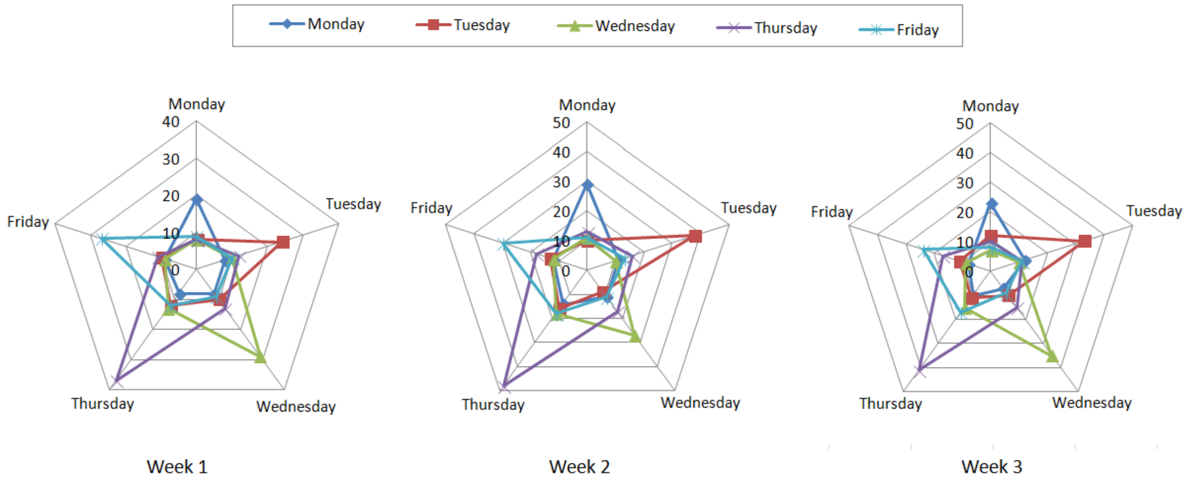


Fig. 6. Radar plot for common WiFi address between weekdays

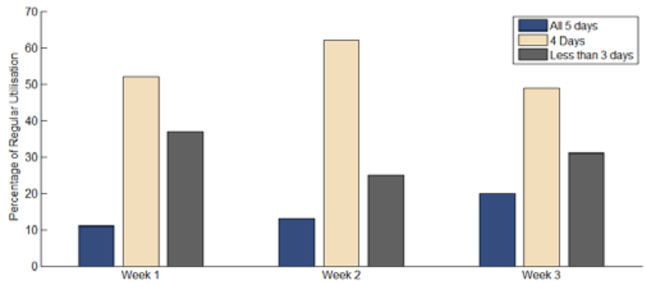


Fig 7. Distribution of the staff attendance of the area along each week

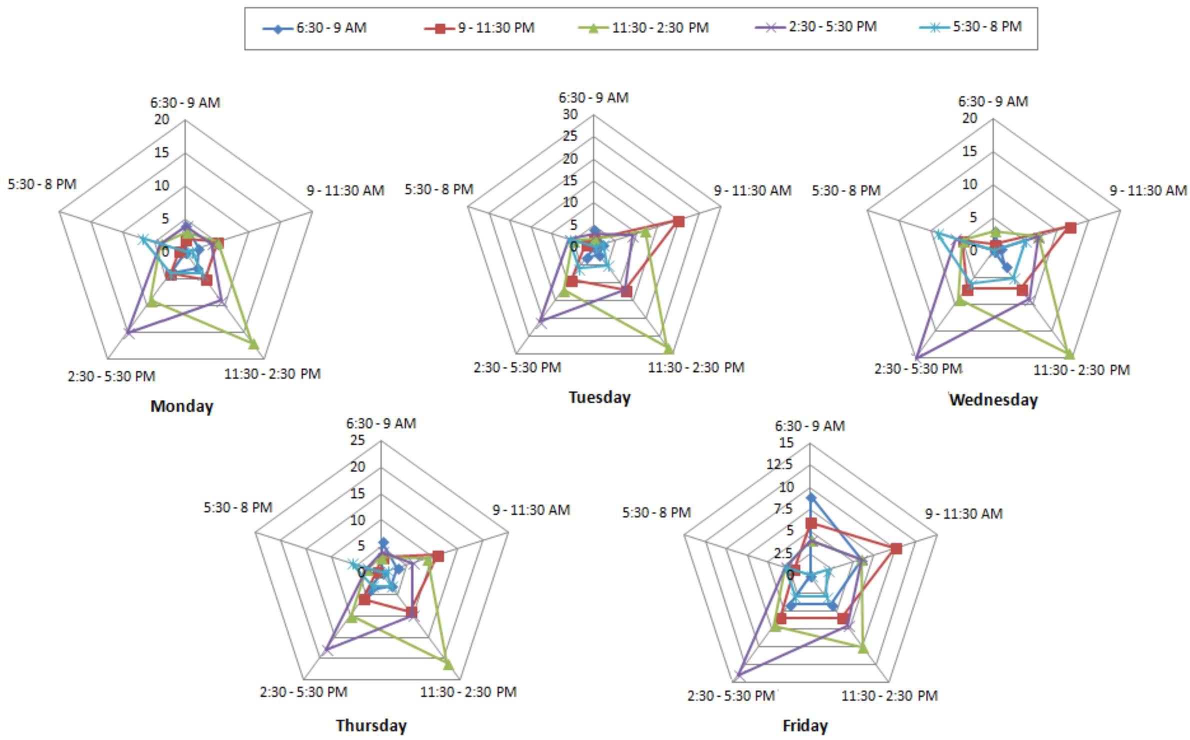


Fig. 8. Radar plot for common WiFi address between different periods of day

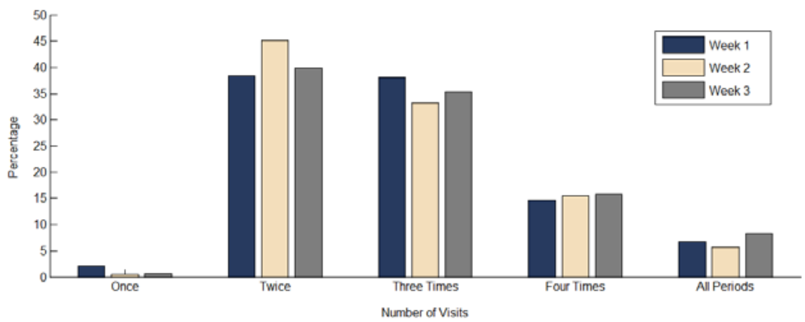


Fig. 9. Frequency of utilisation

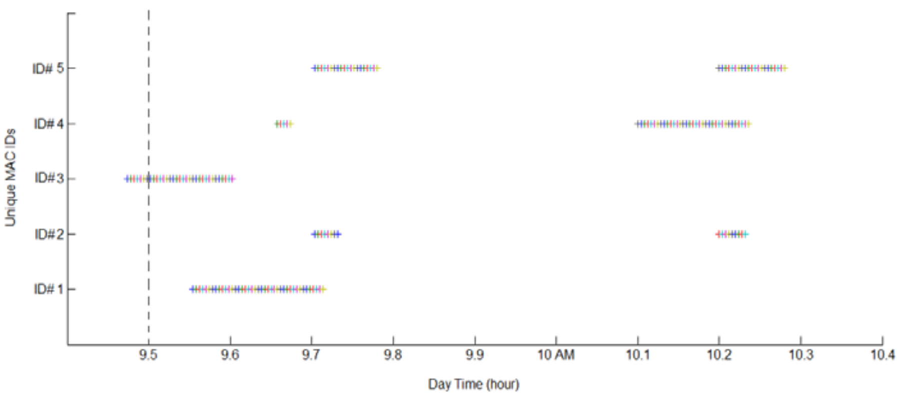


Fig. 10. Example of valid and invalid records for time spending analysis

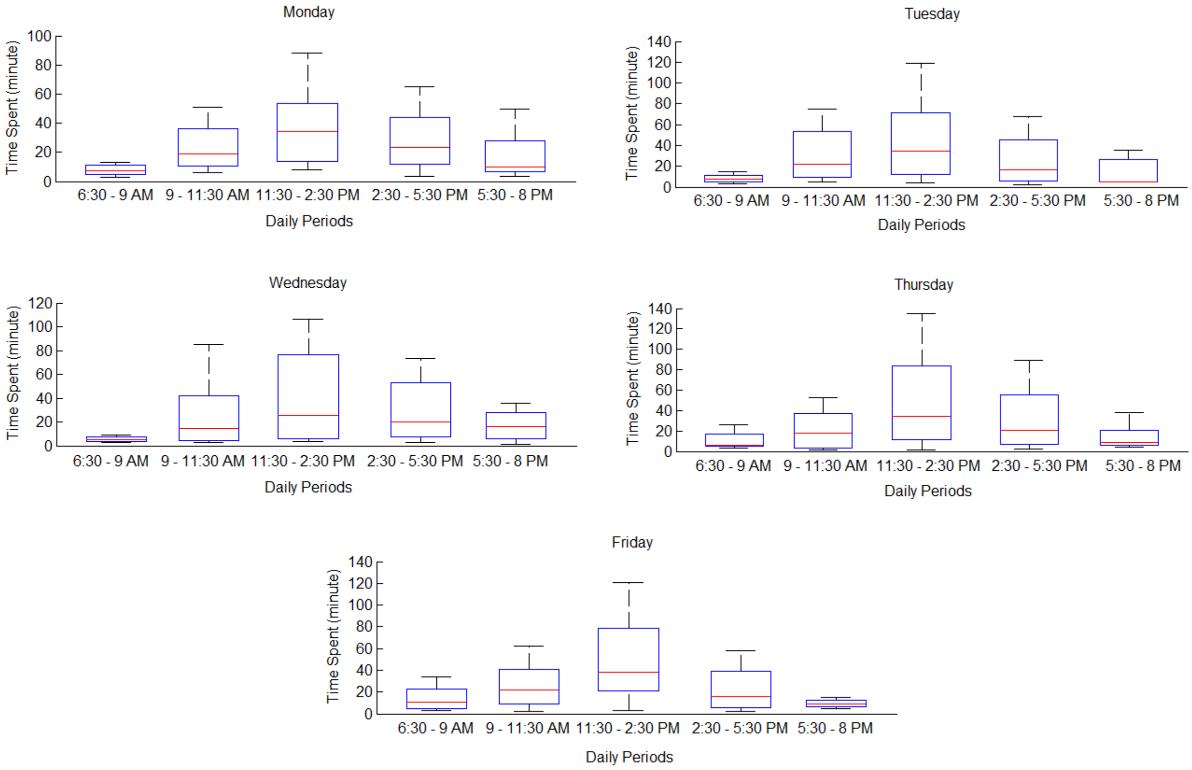
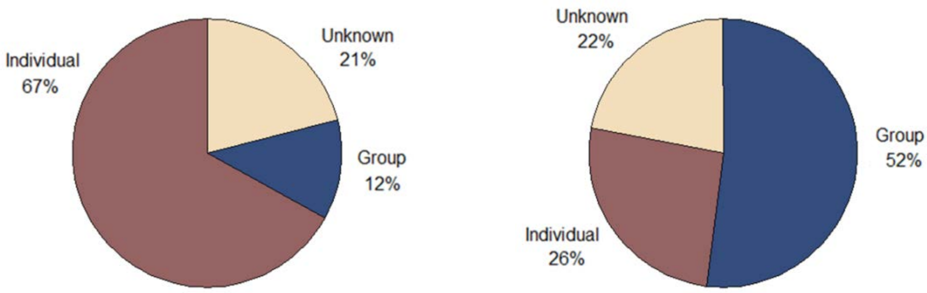


Fig. 11. Frequency of utilisation



(a) (b)

Fig. 12. a) Proportion of utilisation; b) Frequency of utilisation

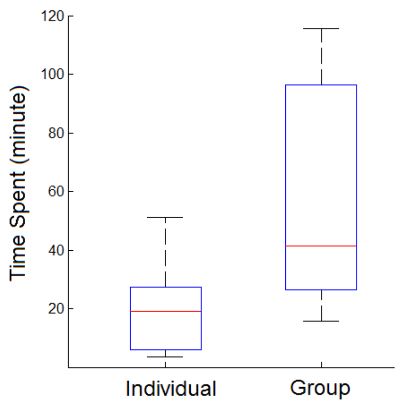


Fig. 13. Group and individual time spending

Table 1
Obstacle severity on wireless signals (Harwood, 2009)

Obstruction	Obstacle Severity	Sample Use
Wood panelling	Low	Inside a wall or hollow door
Drywall	Low	Inside walls
Furniture	Low	Couches or office partitions
Clear glass	Low	Windows
Tinted glass	Medium	Windows
People	Medium	High-volume traffic areas that have considerable pedestrian traffic
Ceramic tile	Medium	Walls
Concrete blocks	Medium/high	Outer wall construction
Mirrors	High	Mirror or reflective glass
Metals	High	Metal office partitions, doors, metal office furniture
Water	High	Aquariums, rain, fountains