S. Chien, S. Choo, M. A. Schnabel, W. Nakapan, M. J. Kim, S. Roudavski (eds.), *Living Systems and Micro-Utopias: Towards Continuous Designing, Proceedings of the 21st International Conference of the Association for Computer-Aided Architectural Design Research in Asia CAADRIA 2016,* 45–54. © 2016, The Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Hong Kong.

ENABELING LOW COST HUMAN PRESENCE TRACKING

Using commodity hardware to monitor human presence in workplaces

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Abstract. Finding automated methods to track the presence of humans can help designers understand workplaces. Methods to understand the patterns of human movement in workplaces using beacons, badges and sensors are being developed. Whilst the results are promising, they can be costly and may require the manual setup of expensive equipment. The Global Positioning System (GPS) is widely adopted due to its high degree of accuracy, however, is inapplicable in indoor environments due to the physical limitations of satellite attenuation. There is no comparably ubiquitous positioning system that can be used to make device-driven position tracking that is specifically adapted to indoor environments. With the increasing popularity of phones, watches and fitness tracking bands with WiFi and Bluetooth connectivity, we explore the potential of these wireless radios as a low-cost alternative to monitor human movement. As the costs of technology continue to decrease, the means to build a low-cost tracker through WiFi and Bluetooth enabled devices in an indoor environment become possible. Furthermore, is it possible to develop a low-cost tracking device using only commodity hardware that is able to accurately automate and record presence in space with sufficient veracity?

Keywords. Movement tracking; workplace environment; wireless.

1. Introduction

Tracking the presence of humans can help designers create effective workplaces (Sailer 2013). This paper describes experiments to determine the effectiveness of a low-cost tracking device in an indoor environment. It describes the advantages and limitations of using such devices in providing understanding of human movement patterns. This in turn, can be used as a tool to inform designers that improve productivity and social interactions in workplaces. Indoor movement research has relied on manual data gathering to track human movement. It is based on speculation, drawing from personal experiences, newspaper stories, early empirical psychological and, sociological studies (Sailer 2009). However, the need to repeat experiments is time-consuming, laborious and involves a lot of manual data (Hillier 1996, Sailer 2013). Methods to understand the patterns of human presence in workplaces using beacons, badges and sensors are being developed (Khoury et al. 2008). Whilst the results are promising, they can be costly and may require the manual setup of expensive equipment (Fleuret et. al. 2008). The Global Positioning System (GPS) is widely adopted due to its high degree of accuracy, however, is inapplicable in indoor environments due to the physical limitations of satellite attenuation (Mautz 2008). There is no comparably ubiquitous positioning system that can be used to make device-driven position tracking that is specifically adapted to indoor environments. With the increasing popularity of phones, watches and fitness tracking bands with WiFi and Bluetooth connectivity, it has been suggested to use these wireless radios as a low-cost alternative to monitor human movement (Mautz 2012, Scheerens 2012). As the costs of technology continue to decrease, building a low-cost tracker that has the ability to detect human movement through the WiFi and Bluetooth enabled devices in an indoor environment becomes possible. The research will: Develop a low-cost tracking device that is capable to establish the presence of humans in an area using WiFi and Bluetooth technology; evaluate the correlation between measured data and reality using video surveillance. Hence determine accuracy and viability of this method.

2. Methodology

The research deploys a tracker device, a low-cost, off-the-shelf component. WiFi and Bluetooth technologies with 'sniffing' software measure the incoming and outgoing traffic. Movement data is recorded when a signal with a WiFi or Bluetooth enabled device is detected and update quickly enough to capture the movement of people into and out of the surveyed area. To evaluate the accuracy of the tracker device, a camera was placed to capture the number of people in the area. The experiment considers a specific attractor point (kitchen) of architecture firm BVN, as it is an open space that constitutes as a main area for social interaction and meetings with project teams. Still there are confounding factors as people being studied may have zero or more transmitting devices with them as they enter the area. This may bias the data, by not counting, or double-counting, a person. A video camera will act as a control to evaluate the impact of data collection during experiment.

Multiple Devices – An individual that may carry a laptop, phone and a tablet at the same time as they enter the area can cause an increase in numbers and bias the counting analytics of the results.

Discoverable Mode – For the agent to collect any data, the WiFi or Bluetooth enabled device must have these wireless connections on. If the user has never accessed the WiFi Access Point (AP) in the past, the packets of data that are sent to detect known networks are not transmitted. This would make the person with the device invisible to the tracker device.

3. Background research

An indoor environment's structure can have a significant impact on the range and accuracy of any tracking device. Several case studies have evaluated a variety of indoor tracking technologies and indicated that accurate estimation of Bluetooth and WiFi localization is a challenge in indoor spaces (Kaemarungsi 2005, Khoury et al. 2008, Mautz 2012). Signal propagation loss is a significant cause of unreliable results, due to different building materials, furniture and radio interference from microwave-ovens and refrigerators. Furthermore, human bodies can interfere with the line of sight between emitter to receiver.

WIFI ARCHITECTURE – The scan involves two methods: Active and Passive. It uses Scan, Authentication and Association procedures (Abbott-Jard et al. 2013). The scan procedure is used for finding MAC addresses in the area whether it may be in Active or Passive mode. During an active scan, the client radio transmits a probe request and listens for a probe response from an AP. During passive scans, the radio listens on each channel for beacons sent periodically by an AP. Once the device has found the AP, it operates the authentication phase followed by the connection. This allows the device to communicate with stations in other BSS's, to which the tracking device can then detect the signal by the tracking device. When a WiFi enabled device is actively seeking to connect to a known network, it can result to two different outcomes. (1) Involves scanning for 'Beacon Frames'. These are packets broadcasted by WiFi routers used in order to broadcast their presence and attempt to initiate a connection with a network that the device has previously connected to. (2) Involves broadcasting packets called 'Probe Requests'. This technique captures data by probing for network by circling through the access points within the area. This can periodically capture the

Service Set Identifier's (SSID) as it determines the closest AP and unique MAC address of the device.

BLUETOOTH ARCHITECTURE – Bluetooth detection has two states - standby and connection. In standby state, the device has no interaction with other devices. In connection state, data can be transferred between devices. Inquiry and inquiry scan are the main parts of the device discovery protocol. A discoverable device runs the Inquiry or 'Master' and Inquiry Scan is run by a device that is willing to be discovered or 'slave'. When the Master receives a packet from the slave, it sends a connect request to the master. Once the master receives the connect request, the devices are connected and can exchange data packets.

With the increasing popularity of smartphones, laptops and portable devices being configured with wireless communication, capturing the emitting WiFi and Bluetooth signals from devices is noticed as an effective crowd data collection and monitoring system (Liebig and Wagoum 2012, Stange et al. 2011). As these wireless communicators are attached to a unique MAC scanners, it can help estimate staff utilization spent time and frequency during different periods throughout the day using a low setup and processing cost. A study evaluated the impact of using MAC address data with WiFi and Bluetooth scanning technology as an effective tool for tracking and analysing human movement in terms of shared space utilization in a staff lounge of an office environment (Abedi 2014). It observed the proportion of staff utilization frequency over the duration of three weeks. The results demonstrate the functionality and significance of MAC data for human behaviour analysis. The results of the study extracted human movement features that are difficult and expensive through other methods such as video surveillance. Video surveillance can be expensive due to the amount of angles needed to track the trajectories of people moving through different frames of the footage (Rassia et al. 2009). In addition to this, illumination changes, limited viewing angles, density and brightness of crowd can hinder the accuracy of the results in office place environments.

4. Implementation

The tracking device consists of (1) two Raspberry Pi 2: Model B devices (RPI), a low cost, credit card-sized computer. It will run Raspbian Wheezy, an operating system optimized for the Raspberry Pi hardware. The RPI requires an (2) SD card for storing the data collected and, (3) a WiFi and Bluetooth USB adapter to capture the signals emitted from WiFi and Bluetooth enabled devices. One RPI is dedicated to capture WiFi signals and the second RPI with Bluetooth signals. It is possible to combine the scanners using one RPI, however, is not currently capable of scanning WiFi and Bluetooth simultaneously. Therefore, for the purpose of this experiment, the scanners will be separated. Three WiFi adapters, TP-Link TL-WN727N, TL-WN722N and TL-WN821N, were evaluated during the experiment. The results indicated that whilst these USB adapters are compatible to connect WiFi to the local network, the TL-WN727N and the TL-WN821N were incapable of supporting monitor mode. Switching to this mode is required to sniff WiFi signals emitted from WiFi enabled devices without associating and connecting to the device. The study was conducted using the TL-WN722N. For Bluetooth, a Cambridge Silicon Radio (CSR) 4.0 USB adapter was used.

To maximize the amount of information collected about the detected devices, additional sniffing software was installed. Aircrack-ng was used to sniff WiFi signals, and Bluelog was used to sniff Bluetooth signals. Aircrack-ng is a network suite used to detect, sniff and manipulate WiFi networks. As clients send out directed and broadcast probe requests searching for AP they have connected to previously, Aircrack-ng has the ability to capture their unique addresses which can be displayed through two of its tools - airmon-ng to display probe requests and airodump-ng to record the data into a readable csv file. Bluelog, the second sniffing software, is a free Bluetooth scanner that is designed to capture and analyse the traffic of discoverable Bluetooth devices there are within a given area as quickly as possible. Intended to be used as a site survey tool, it prioritizes detecting the number of discoverable devices than device specifics. However, given the ability to identify MAC addresses of discoverable devices, this information can be used to assess the traffic of people in an area.

5. Experiment

This section presents real-world experiments to test whether it is *possible* to use commodity hardware as a technology to track the presence of humans in an indoor environment with sufficient veracity. The experiments are divided into four tests. The data and information collected as a result of each test is analysed and evaluated.

EXPERIMENT 1: TRACKING USING ONLY HARDWARE. The initial experiment was done to primarily evaluate the effectiveness of the device as a tracking tool prior to the installation of any sniffing software. The experiment was conducted for ten minutes with each RPI device needing to only detect one smartphone and one laptop device in a small, four by four meter room. The results for Bluetooth were simple. The RPI was able to detect the Bluetooth enabled smartphone and laptop within 5 seconds of running. It was able to gather basic data about the device - MAC address and 'friendly' device name. Whilst the results for Bluetooth successfully capture the presence of different types of devices, however, it does not track the outgoing traffic from the area. Therefore, the data assumes that the human is in the area from the time the signal is detected until the termination of the test. Furthermore, as it detects two devices with two different MAC addresses, it also assumes that there are two people in the area. This can cause an inaccurate collection of results when evaluating the presence of humans in a more populated indoor environment. WiFi is able to actively detect access point connections using 'iwlist scan'; unfortunately, there is no equivalent command that passively scans for devices. Therefore, the test could not be completed without the use of software. A second test was run, again for 10 minutes. The laptop was positioned in-between the RPI and the smartphone. The signals emitted from the phone were unable to be detected due to electronic interference throughout the duration of the experiment. In order to limit and reduce the chances for signal propagation loss, it is imperative that the RPI is positioned in an open area away from physical objects that can interfere and impact the results of the data collection.

EXPERIMENT 2: TRACKING WITH SOFTWARE. This involved running a test with each RPI with the sniffing software in the kitchen area of the architectural office. The test is conducted for one hour; during the lunch period. A video camera is strategically placed in the corner of the kitchen to ensure each person that enters of the area is captured in the frame to evaluate the accuracy and viability of the experiment. Bluelog and Aircrack-ng are initiated simultaneously. Airodump-ng allows filtering information, only collecting information that is relevant for the experiment. This experiment is configured to detect MAC addresses, signal strength and timestamps of the detected device, which is logged to a txt file as they are observed. Bluelog is also capable of filtering sniffing commands to collect required data for the experiment and logs the information into a csv file. This experiment is configured to detect the MAC address, device class and friendly name of the device, timestamp. Bluelog is run in amnesia mode to force it to detect all present devices each time step. This allows us to measure the approximate length of their presence in the kitchen by assuming that a device that is present for contiguous 4-second blocks hasn't left the area. The results revealed that both Bluelog and Aircrack-ng was unable to detect the presence of every person incoming and out of the kitchen area. An overall total of 55 people were detected in the video frame throughout the duration of the experiment. Only 33 WiFi devices were detected, approximating to 60%. However, as four people are shown to have a laptop and phone each, the data assumes that there are a total of eight people when there are only four in the video. Results also revealed that the data gathering process for Bluetooth was delayed in comparison to Experiment 1 due to the amount of information it was configured to collect for a higher volume of people. This can hinder the evaluation of results when trying to collect real-time detection and approximated length of an individual's presence in the kitchen. Further, it also concludes that the popularity and signal availability of WiFi enabled devices is higher in comparison to Bluetooth. Although, the WiFi detection rate was not accurate, there is a 43% difference of data detection between both wireless signals.

EXPERIMENT 3: SPEEDING UP THE PROCESS TO COLLECT REAL-TIME DATA. This will be a repeat experiment followed by Experiment 2. Due to the slow detection rate when attempting to collect real-time data, the amount of information that will be collected from Bluetooth detected devices will be less. The class code of the device, the type of device and signal strength information is removed. The MAC address of the device and the timestamp will be the only information collected during this experiment. The results were slightly more efficient. Removing the type of device and signal strength increased the detection rate of Bluetooth devices. However, the results were not significant as it continued to present a low number of results in comparison to the presence shown in the video.

EXPERIMENT 4: SPIKE OF PRESENCE. This experiment was conducted during a surge of human presence. On Thursday afternoons, at exactly 4pm, the majority of the office gathers in the kitchen to collect sweets. Prior to this experiment, it was assumed that people will either not have their devices on them as this is a very short burst period or the tracking device will not detect the wireless signals in time. The results during the spike of presence indicated that there was an insufficient amount of data collected. The graph in Figure () indicates that at 4.01pm, only 42% of people with WiFi enabled devices were detected. This could be caused by two factors – signal propagation loss due to the high volume of people interfering emitting signals or people not carrying a device as they enter the surveyed area. Both factors have significantly affected the data, to which can conclude that using a low-cost tracker through WiFi and Bluetooth enabled devices is not efficient to monitor high volumes of human presence in a quick amount of time. Detecting Bluetooth signals throughout the duration of the experiment also displayed a significant amount of inaccuracy. At each 5-minute interval of the graph, it is evident that no more than 2 Bluetooth devices are detected at a time. However, we can conclude the popularity of using such wireless devices with people choosing to enable their WiFi device over Bluetooth.

6. Conclusion and future directions

The main objective of this project was to determine whether a low-cost tracking device using commodity hardware was able to accurately automate and record presence in space with sufficient veracity. This conclusion presents an evaluation of the correlation between the collected data and reality using the video footage. It also presents the limitations and drawbacks that were encountered throughout the process that impacted the data gathering experiment. A low-cost tracker using commodity hardware *can* be used as a tool to monitor human movement to evaluate space utilisation behaviour. The assessment of compatible and effective hardware and software tools was required to gain an understanding to build a low-cost tracking tool that efficiently and appropriately scanned WiFi and Bluetooth enabled devices using inexpensive products. Evaluation of Bluetooth and WiFi popularity revealed that WiFi signals are more numerous than Bluetooth. This suggests that we can be more confident in data collected from WiFi signals than Bluetooth.

To point out limitations and drawbacks, it can be concluded that the integration of WiFi and Bluetooth in devices can be used as a human movement-tracking tool. It was able to detect nearby devices, however still presented significant challenges in indoor environments when attempting to detect real-time and accurate data.

Not Carrying a Device – The absence of an individual's device/s as they enter the surveyed area hindered the counting analytics of the data. The comparison of the video footage from Experiment 2 indicated that during short and quick moments of an individual walking through the kitchen, a device was not detected. The results concluded that out of the 55 people that were captured in the frame throughout the duration of the video, only 29 WiFi enabled devices were detected, approximating to 52%. A total number of 9 Bluetooth devices at the conclusion of the hour were captured, approximating to 16%. The significant number of inaccuracies can propose that the development of the low-tracking device is unable to accurately measure and identify the amount of human presence in an area that is prone to constant and quick incoming and outgoing traffic.

Multiple Devices – An individual that may carry a laptop, phone and a tablet at the same time as they enter the area can significantly hinder the analytics of the data. During experiment two, the tracking device was able to pick up 4 individuals with each interacting with a phone and laptop in the kitchen. The data assumes that there are a total of eight people in the area when in fact there were only four.

Observing and evaluating the utilisation of space can be beneficial to businesses. Understanding the occupancy of spaces throughout an office place can help inform designers and businesses to improve existing design interventions in order to increase productivity, social interaction and business progression. It can also help analyse the density of flow and circulation throughout a space and evaluate the use and need of spaces in workplaces. By identifying the significance and peak periods of the utilisation, it can inform designers to find methods to optimise the performance of productivity. This kind of knowledge from human behaviour can facilitate them for the implementation of future plans with minimal risks involved. In another aspect, the results can be useful for human resources, helping those to understand the social interaction between people. This can help guide them to set up plans for the enhancement of social activities when organising events.

In order to progress forward from tracking human presence, one can start to localise the position of an individual through the process of triangulation. Triangulation has the ability to locate the position of the user by converting the Received Signal Strength (RSS) to a distance measurement between AP's and the user with the device. Three or more tracking devices are required to determine an accurate position of the user. This triangulation method will start by calculating the distance from the each closest base station to the user, which is then used as the radius from the station. As a result, the location is then assumed by pinpointing the area of the overlapping circuit and translates the user device to X and Y coordinates in space.

With only one Bluetooth, and one WiFi tracking device deployed at an architectural office, only basic information that can help detect the amount of devices could be collected. Installing various devices throughout the office can allow for advanced analytics with localisation and positioning strategies. Localisation analytics can help understand the behaviour of individuals in workplaces. As Space Syntax studies rely on manual data to track the patterns of human movement, using an automated metric data system can help speed up the process using inexpensive technology when comparing the expense to beacons, fitness bands and sensors.

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