PROXIMITY DETECTION USING A WIRELESS EMBEDDED SYSTEM

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1.0 INTRODUCTION

1.1 VISION FOR THE FUTURE

Analytics of human movement is used to identify queue times, dwell times and person count. This data highlights trends of how people use a space, although it does not explain why. The data could be used by airports to identify busy times, retail to arrange better staffing and public transport to improve services.

Current solutions for the detection of human presence are typically either active or intrusive and detract from a users experience. On one hand, only a minority of users will provide verbal, digital (like an app on a mobile phone) or physical feedback to an operator. Active participation can be seen as frustrating since users do not tend to see the impact of their feedback. On the other hand, passive tools such as counting floor mats or lasers can involve expensive infrastructure and setup.

An ideal solution would be accurate, non-invasive and cheap. If a business can receive accurate, real time information on the state of their customers then they are able to provide a better service.

1.2 AIM OF PROJECT

This project aims to develop a system for detection of nearby wireless devices that can model an estimation of the number of people present in that space. The project will be developed using a modular approach, whereby sub-systems are scalable for simple redeployment. The outcomes of this thesis will enable others to further develop accurate means for tracking people wirelessly using their mobile phones.

An embedded system will be developed to monitor a room using wireless technology in order to count the number of devices in the vicinity. The embedded system must be easy to use, scalable and cost-effective. The number of detected devices will act as a basis for how many people are nearby at any one time. The relationship between mobile phones and people will be investigated to develop an accurate model for counting people. How people use their phone and the phone's interaction with wireless networks will affect this model.

The developed model will be tested to see how it performs compared to other existing solutions. How different parameters affect the data needs to be quantified, since variables can play a key role in determining the ratio of phones to people. For example, it is already been demonstrated that a number of objects obscure wireless signals, so how the propagation of signals is affected by location needs to be explored.

1.3 DELIVERABLES

The two main deliverables are the embedded system and the model. These deliverables will be separate to provide an opportunity to further develop one or both. There will be two series of experiments, firstly to quantify a model and secondly for validation.

The first deliverable is an embedded system that listens to nearby wireless traffic and then broadcasts a summary. It will listen to an environment and attempt to count the number of unique mobile devices. This information will be broadcast for further analysis and modeling.

Secondly, a model will be developed to quantify the ratio of mobile phones to people in a variety of environments. This will be developed after a series of experiments comparing the captured wireless data and a manual count. A second series of experiments will then evaluate the output of the model to validate its accuracy.

1.4 REPORT OVERVIEW

This proposal outlines literature relevant to wireless tracking of humans, as well as a plan to develop an embedded system and accurate modeling technique. While this proposal outlines the current strategy, it is may change over the course of the year.

Literature for this research is broken into three sections. Firstly, a review of literature is undertaken to localize or use proximity to detect a person. Secondly, the literature relating to what technology has been used to track proximity or localize devices in a space will be examined. This encompasses both indoor and outdoor environments, with a focus on the former. Lastly, a review on how individuals have been counted using mobile phones will be undertaken. The importance of this and its potential future applications are also outlined.

A plan that outlines how to achieve these objectives is presented so that progress can be measured. Potential technologies that can be used to detect people and their devices are listed and compared. Methods on handling and analyzing data are also discussed. An initial list of environments to develop and test the model is proposed. Finally, the criteria of a successful thesis are listed.

2.0 BACKGROUND

2.1 PROXIMITY OR LOCATION

Data on a crowd's movement is significant to both operators and users. Knowing how many people are present and how they are interacting with their environment allows better service for the user and lower costs for the operator. However, "proximity and localization of activities and people are two notions that are often mistaken for one another" [1]. Torre A. and Rallet A. [1] have distinguished the two, and note the "semantic wealth of the notion of proximity". Namiot D. and Sneps-Sneppe M. [2] also suggest that "in many cases, the concept of location can be replaced by that of proximity". Further, since indoor localisation has resolutions of a few metres [3, 4] it is difficult to make both scalable and accurate.

Operators tend to need only the number of people present. The number of people in a public transport system, or in a shop is sufficient for the majority of operators. Localisation of individuals is substantially more difficult, requires a higher start-up cost and is not easily scalable.

2.2 PERSON COUNTING METHODS

There are a number of ways to count humans. These can be broken into 3 types of data collection techniques.

- 1. Manual counting. (Example: Having someone count).
- 2. Physical interaction. (Example: Turnstile).
- 3. Wireless Technology. (Example: Video camera).

Before the rapid expansion of information technology, person count data was only able to be collected using other humans [5]. Manual counting is expensive, in addition to facing area and time constraints. Further, data such as repeat visitors and length of stay are difficult to gather. A study by Bauer et al. [6] found that humans under count by between 8-25%. They noted that the complexity of the scene, the flow rate, width and number of lines could all affect how accurate a count is. However, they did note that manual observation does not require much planning and is hence a fast means of obtaining data.

Person counting expanded to a number of physical interaction barriers and these include laser beams, turnstiles and floor mats. A second study by Bauer et al. [5] investigated the use of switching mats and light barriers in an airport in Vienna, Austria. They used the mat and light barrier to estimate the number of people moving through the airport security line. The data indicated that the switching mat over estimated by 12.5%, and the light barrier by 12.6%. The data was more accurate after using a calibration factor, however there was still large error even at low counts. Further, the costs of the laser/light barriers were between \$50 and \$100, while a 75cm by 1m mat was \$1500.

Hernndez-Soza et al. [7] also investigated the use of a laser beam and webcam to count the people entering and exiting through a controlled area. Using a cheap video camera and a light barrier, they managed to accurately detect 90% of individuals entering and exiting a space. Similarly to Bauer et al. [6], they managed to collect within 10-12.6% of events.

Using a video camera is another common method for counting people. This technique is used to count traffic [8-11]. As seen in the case of Stilla et al. [8], where a satellite camera was used to look down from above to count cars. By identifying individual cars, they were able to gather data about traffic flow. This data did not specifically identify individuals but was still useful to gauge how roads were being used. Stilla et al.'s [8] system managed to correctly identify vehicles 87% of the time, although vehicles were completely identified only 60% of the time. This is consistent with Bas et al.'s [11] finding. They also used a camera to detect the flow of traffic with an error of 11-16%. Lefloch et al. [12] were able to develop a blob counting system, whereby image recognition techniques identified people as blobs in order to be counted. When the area had greater crowd density the data became inaccurate, as the system was not able to distinguish one person from another. Also Lefloch et al. [12] only used a single camera, which resulted in blind spots. A "better camera" and "motion tracking" could overcome these issues, although this will add increasing complexity.

Radio frequency tags (also known as RFID) have also been used as a solution to monitor people indoors. Active tags are very cost effective [13] and can be "read despite extreme environmental factors, such as snow or fog" [14]. They use an inbuilt battery that can last 3 to 5 years and allow an RFID scanner to detect 500 tags up to 45 metres away in 7.5 seconds [14]. However, passive tags have a very limited range of approximately a metre and require numerous scanners [13]. Both active and passive tags are application specific and would require users to carry the tags for data to be gathered.

2.3 PERSON COUNTING USING MOBILES

Considering 90% of Americans have a mobile phone, counting people using mobiles seems reasonable [15]. As a result, it almost seems safe to assume that for every mobile device found, one individual is present. This is not the case. Laptops and tablets in addition to mobile phones may broadcast their Bluetooth, Wi-Fi or other wireless data. Further, a phone is only in arm's reach an average of 58% of the time according to Patel et al.[16]. Therefore, the assumption that one device equals one person does not always hold. In spite of this, there are still methods to count people using their mobile. This typically involves a mathematical model to convert device number to person count. Usually this is dependent on location, demographic and system used.

A simple approach is to measure the number of visible Bluetooth devices. Bluetooth is already being used to estimate crowd density at football stadiums, in retail and at public festivals. Most mobiles however, have their Bluetooth status set to undiscoverable and only about 2-7% of mobile phones are visible by Bluetooth [17, 18]. This is still useful however, since the correlation of Bluetooth devices to people is fairly high, R²=0.89 [17]. Bluetooth does have limits of 33 devices per scan, 11 seconds per scan and a range of 10 meters [17-19]. Bluetooth is useful to identify individual devices since they can broadcast their MAC address. This allows a system to identify repeat visitors, or measure the time a person takes between two points. A three day experiment at Oktoberfest in Munich found an 80% accuracy using Bluetooth [20]. They did notice that using Bluetooth they "had to consider cultural factors" and the model of device to person "may significantly vary depending on who the persons in the crowd are [20]."

Wi-Fi is the other main wireless system on most mobile phones. Counting the number of people using Wi-Fi has been investigated before [13, 21, 22]. Over 90% of mobiles are Wi-Fi enabled, making it the most used wireless communication [23]. Xi et al. [21] describes the benefits of using mobile devices rather than images and cameras. Cameras "cannot work well in a dim or dark environment", and RFID or tags "require every human being to carry the device, and are inaccurate and unreliable in practice". Wang et al. [22] used a system to measure the strength of the Wi-Fi signal from the front of a queue. Judging from the increase in signal strength over time, they were able to see how quickly a queue moved.

Kannan et al. [24] used audio tones to estimate a crowd. They figured that a crowd counting system should be easily deployed, scalable and energy efficient. Further, to minimize impact with the crowd, the system should be "minimally intrusive to the user". They determined that a large portion of the crowd possesses a mobile phone and their solution would be less intrusive to use than RFID or tags. They found that audio tones were 82% more energy efficient than Wi-Fi. Their solution allows phones to communicate over 98 frequencies, and spaced at 5m² per device results in 19600m² of possible area that can be covered. A disadvantage is that their algorithm may result in multiple devices picking the same frequency or phones being unable to generate certain frequencies. In conclusion, their solution had an accuracy of 80%, which was not as accurate as laser beams or cameras.

2.4 SUMMARY AND RECOMMENDATION

Based on the reviewed literature, a Wi-Fi based passive system that is cost effective, accurate and scalable will be developed. The two main choices are to detect the proximity of people and to use Wi-Fi.

Whether it be to monitor the state of a public transport system, event planning or in retail spaces, knowing the number of people present can improve service and user experience without including users specific location. Systems using Wi-Fi [25, 26] and Google Maps Indoor [27] have already been used to localize people. However these techniques tend to have poor resolution and are only accurate to within a few square meters. Further, a user's location is more useful to himself or herself than the operator. The person count using proximity is a better practical choice.

The choice to use Wi-Fi is the other major decision that was made. The other contender was Bluetooth. Considering the limits of Bluetooth, Wi-Fi is more scalable because of its range. Bluetooth has less range, has a smaller limit of devices per scan and has a smaller percentage of discoverable users. The only other wireless method is video camera, which is just as accurate and is limited to certain times and will inevitably have blind spots [7, 8, 10-12]. While more unique methods such as audio tones have demonstrated accuracy [24], these are not as scalable as Wi-Fi. Further, physical interaction from users on floor mats or through lasers tends to have about the same accuracy as wireless devices [5-7].

This will therefore develop a Wi-Fi proximity person counter. The accuracy of the device will be trialed and tested in a number of environments, with different crowd characteristics to determine whether there is a suitable model.

3.0 DESIGN

3.1 SYSTEM OVERVIEW

A three component system using a Raspberry Pi that sniffs wireless traffic, an Message Queue Telemetry Transport (MQTT) service and a modeling system (Figure 1) will be developed. The data analysis and modeling will not be done on the Raspberry Pi, so that other models can be applied to the microcomputer's output. Secondly, an MQTT server that receives and handles the messages will be used to allow the messages to be analyzed anywhere. Lastly, a modeling system, which receives the data over MQTT and models it to estimate the number of people, will be developed.

MQTT Server Wi-Fi Rasberry Pi Modelling System

Figure 1: System Diagram

3.2 EMBEDDED SYSTEM

An embedded system, which listens to the Wi-Fi of an area, will be developed. A Raspberry Pi seems to be the most suitable. It can run an operating system, has networking capabilities and is a popular platform. The Raspherry Pi does not have built in WiFi, however a small USB dongle will be attached to provide it with this capability. The Raspberry Pi will run software that will sniff Wi-Fi packets nearby.

Wireshark is an open source packet analyzer. When promiscuous mode is enabled it is able to see all packets travelling on the same network [28]. If an access point is already established, and the Raspberry Pi is connected, it would be able to see packets sent from other nearby Wi-Fi devices to the access point. Filtering the results to obtain only the unique MAC addresses would obtain a device count. Wireshark however has a graphical interface and while it can output its captured data, must be done by the user. This means that Wireshark would require frequent interaction and is not able to pipe its real time output to another system or process.

Tshark is the command line equivalent of Wireshark. It is able to apply all the same filters of Wireshark but from the command line, without a graphical interface. Tshark has been run on Raspberry Pi before to sniff packets [29]. The advantage of using TShark over its graphical interface twin Wireshark, is that it can pipe its output to another Unix process.

Kismet is a console based wireless network sniffer. It can "de-cloak non-beaconing networks" and "detect IP blocks by sniffing TCP, UDP, ARP, and DHCP packets" [30]. Kismet has previously been used to detect the presence of nearby Wi-Fi devices [31]. Kismet is able to pipe its output to another process, which could then transmit data over wireless.

TCPDump is a command line network analyzer. It can be used to monitor a network, and filter types of packets. It has also been used on Raspherry Pi before [32]. It would be capable of filtering packets addressed to an access point.

All of the above mentioned tools could do a lot of similar tasks. Further, a number of them can be run from the command line and have filters applied. *TCPDump* and *Kismet* are more lightweight but does not have as many tools and filters as *Wireshark* or *Tshark*. All will be trialed on the *Raspberry Pi* to determine which is most suitable to count unique devices (via their MAC address). The data gathered will be piped in real time over a network to model and estimate the number of people nearby.

3.2 HANDLING DATA

The embedded system will only obtain a count of unique devices in the space nearby. The *Raspherry Pi* will not perform any analysis or modeling on the data it collects. The unique device count will be transformed into a message and transmitted to an MQTT server.

Currently there is an MQTT based server in the Centre for Educational Innovation and Technology, which will be used to handle the data. The messages will be attached with a header so that other systems on the network can use the information if they choose, since a variety of other message types will be transmitted.

The type of system that receives the data is not critical, however almost any device, such as a laptop would be a suitable. After receiving the data, a program will attempt to model the data, estimating the number of people in the space. The estimation is then displayed as a range and will show the person count over time.

3.3 MODELING DATA

A variety of experiments will be performed to investigate how best to model the number of people in a space given a number of active Wi-Fi devices. There has been studies that show 90% of individuals have Wi-Fi active smart phones [15], but only 58% are within arms reach at any time [16]. Both studies acknowledge that these statistics change based on demographic, location, age and numerous other factors. The model must account for as many parameters as possible.

There do exist models, which already achieve accuracy within 10-15% of number of people, therefore the model from this thesis should aim to be more accurate. The model can produce an estimate as a range, but not so broad as to be imprecise.

4.0 PLAN

4.1 PROJECT

The thesis has a number of key milestones and assessment over the course of a year. A plan has been developed to assist in planning and checking to see whether it's on track. The pieces of assessments are:

• This project proposal. Due: 4pm 2 April

• Seminar and seminar attendance. Due: 18-22 May

Poster and Demonstration. Due: 23 October

• Thesis. Due: 4pm 9 November

It is important to develop a plan early. Unlike previous university study where there is frequent assessment, this has assessment 17 weeks apart. Without a plan, to keep on track, progress will be lost.

The main two tasks for the thesis are to develop the embedded system and to develop a model. These tasks along with the assessment have been placed in a Gantt chart (Figure 2). This Gantt chart is the initial plan, and will inevitably change over the course of the year. Whether tasks become blocked, or a solution becomes unviable, dates will move. It is still important to remember the scale of thesis and to try and follow the Gantt chart to some degree or milestones will not be met.

Date Task 16/03 6/4 27/4 18/5 8/6 10/8 31/8 21/9 12/10 29/6 20/7 2/11 Thesis Idea Proposal Develop Test Seminar Poster Demo Thesis

Figure 2: Thesis Gantt chart

4.1.1 TECHNOLOGY

The technology side of the project is relatively simple and can be based on previous projects. Using Wi-Fi to estimate crowds has been done before [21, 22, 24] and the technology to monitor network traffic on a Raspherry Pi is not new either [29, 32]. However, from a review of the current literature, counting people using a wireless embedded system appears to be innovative.

Since these individual technologies are not completely new ideas, they should be easy to implement. The extension of existing approaches is applying network-monitoring software to an embedded system and filtering and transmitting the data. In line with the estimated difficulty of this task, the Gantt chart (Figure 2) shows developing technology as a relatively short period of time.

The resources required to develop the embedded system are the *Raspberry Pi* and Wi-Fi dongle and are critical to the thesis. These are already available in the laboratory, allowing development to commence shortly. The embedded system is critical to the thesis, which is why the deadline for its completion is early in the year. The two milestones encapsulated in this embedded system are, firstly, to count the number of unique Wi-Fi devices in a space and secondly, to transmit the data over MQTT.

4.1.2 MODELLING & INVESTIGATION

Modeling the gathered data will be the largest part of the thesis. Studies have already achieved accuracies of within 10-15%. Physical barriers tend to over estimate while passive technologies tend to underestimate. This thesis should aim to be more accurate. Patel et al. [16] showed that users are not always near their mobile phone. They also showed it carried greatly depending on a number of parameters. What these parameters are and how they affect the model is at the core of this thesis.

Experiments will have to undertaken to see what parameters are affecting devices detected. Some experiments that might be undertaken include:

- Indoor and outdoors.
- Day and night.
- Morning and afternoon.
- Wi-Fi access available and not available.
- Crowded space and empty space.
- Type of room.
- Quantity of Raspberry Pis collecting data.

The three resources required for this part of the thesis are the time taken to undertake experiments, a person to manually count, and the embedded system. The two main resources required for these experiments is a person to manually count and the time needed. Each experiment could take some time. The manual counting and verification of data is time consuming. The number of experiments and their duration has not been decided either. The other resource required is the embedded system, without which, no experimentation can be undertaken.

Using the information gathered from a series of experiments, a model will be developed to estimate the number of people in the space. The first milestone, the series of experiments to develop a model, will be finished by the end of the mid-semester holidays to allow time to verify and evaluate it. The second milestone, verifying the model, should be finished by the middle of the second semester. The model will then be tested to determine its accuracy. This will involve a second series of experiments in similar and different scenarios to the previous experiments to determine a model. Its accuracy over time will be recorded.

A large part of the thesis has been allocated to data collection, verification and developing a model. As seen in the Gantt chart (Figure 2), it should take up the majority of the year. The model and the accuracy of the system will be the main presentation in the final thesis.

4.2 OCUPATIONAL HEALTH AND SAFETY

This development of the technology for thesis will be undertaken in a low risk laboratory. Consequently the OH&S guidelines are the standard lab rules. The only exception to this may be the experiments to gather data and validating the model. Since these locations have not yet been determined, no OH&S assessment has currently been made. Nonetheless, a risk assessment will be undertaken prior to each experiment.

4.3 DETERMINING SUCCESS

Numerous technologies, models and experiments could be explored for this thesis. Therefore it is important to set some limits and determine when the work is sufficient. The criteria to determine success is considered to be the following:

- 1. An embedded system and model, which accurately estimates the number of people in a space with less than 10% error.
- 2. If no suitable model can be found, identifying factors that prevented this from being reached and improvements that could be made.

The model and system should also be cost-effective and scalable. Analysis of the solution will also be performed to determine whether it meets these criteria. If the system and model fail to meet these criteria then it will hardly serve as a new solution to counting people.

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