SOCIAL DENSITY ESTIMATION BASED ON CONSUMER SMARTPHONE SENSORS

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a thesis on the topic of Computing Science

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January 2017

[December 10, 2016 at 21:16 – classicthesis version 0.1]

Guntur Dharma Putra: *Social Density Estimation Based on Consumer Smartphone Sensors*, a thesis on the topic of Computing Science, © January 2017

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LOCATION:
Groningen

TIME FRAME:
January 2017

To my beloved family.

ABSTRACT

Estimating social density may come useful for several occasions. Thus, several methods have been proposed to tackle this issue. However, the methods are still not able to deliver really accurate result compared to manual counting of people.

This research presents the correlation between number of unique devices and available Access Points in a particular location. WiFi probe-request is used to determine the unique devices. Furthermore, a cross-validation by using voice activity detection is used to determine whether a person is present.

ACKNOWLEDGMENTS

First and foremost, I would like to express my deepest gratitude to God, the Almighty, for having made everything possible and giving me the strength and courage to finish this work.

I would also like to express my sincere gratitude to both of my supervisors Prof. Marco Aiello and Prof. Martien Kas for the continuous support with my thesis, for his patience, motivation, and immense knowledge. I would also like to thank daily supervisor, Niels Jongs, who has been guiding me throughly until I can finish this thesis.

Last but not the least, I would like to say thank you for my family: my parents and my sisters for supporting me spiritually throughout working on this thesis and my my life in general. Also, my friends and colleagues in Groningen who helped me to work on this thesis.

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LISTINGS

ACRONYMS

AP	Access Point
BSSID	Basic Service Set Identifier
FOV	Field of View
MAC	Media Access Control
PKLV	Peak Level
RMS	Root Mean Square
ROM	Read Only Memory
RSSI	Received Signal Strength Indicator
SA	Source Address
SN	Sequence Number
SSID	Service Set Identifier

1 INTRODUCTION

Social density estimation, or sometimes referred as crowd counting, is the mechanism of estimating the number of people in certain area by means of a proxy, which could replace the manual counting method. It has broad range of implementation, for instance crowd surveillance [20], evacuation and rescue [3], retail store customer analysis, infrastructure development and evaluation, queue management [33], and even in objective behavioral monitoring, especially to estimate the level of social density a patient experiences in more accurate manner.

Several method of social density estimation exists. Surveillance camera utilization is one of the method used, although it is limited by high deployment or computational cost. Other than image based estimation, some researches have proposed Radio Frequency RF signals, e.g., WiFi or Bluetooth, mainly to get more low deployment or computational cost.

The WiFi and Bluetooth based methods make use of several characteristic present in WiFi or Bluetooth, such as probe-request, MAC address monitoring [cite], Received Signal Strength Indicator Received Signal Strength Indicator (RSSI) [cite], Link State Indicator (LSI) [cite], and Channel State Information (CSI) [cite]. From all of those methods, WiFi probe request seems promising, as it is also proven to be able to give social density estimation with high accuracy []

However, doing RSSI in smartphone directly is impossible, as it requires root permission nad rooting is illegal according to most countries' law. As extension of research BeHapp.

define what social density is.

This study serves as

To uncover the relation between the number of unique devices and available access points, I formulated the first research question:

> *Is there any correlation between number of unique devices and number of available Access Points in a certain area?*

When the data is captured, several parameters are also used, such as location, time of scanning, duration of scanning, MAC address filter, and so on. Here comes the second:

> *How do the parameters affect the correlation result?*

As mentioned previously, MAC address randomization is one of the challenges of estimating nearby unique device using probe-request. The third research question is somewhat related to that:

Is there any method to overcome the MAC address randomization issue? Which affecting number of unique devices.

Furthermore, the validation using sound is also used and the last research question is asking about the effect of it.

How does validation using Voice Activity Detection help to achieve better result?

is access point suitable as a reliable proxy for social density estimation?

The rest of this thesis is structured as follows. Chapter **??** describes the related works, which are closely related to the social density estimation.

2 LITERATURE REVIEW

In this chapter, several works that have been done with regard to estimating social density are presented. The approaches are also compared one another, focusing on the benefits, drawback, and challenges. The methods range from video monitoring, audio tone tracking, and RF signal sensing. Furthermore, more implementations of WiFi signal beyond crowd counting are also presented. In the end, a proposed work is portrayed, which is going to be the topic of this research. Some researches have been done with regard to estimating social density, especially more are focused on crowd density.

This is the intro of the chapter.

It is not possible to do probe request in mobile phone [cite]

A good example: https://www.kismetwireless.net/android-pcap/ But it requires a USB NIC that supports monitor mode.

Bluetooth is only possible to count crowd, or estimates. Because it is counting only within 10% of real people count. [cite]

Make sure to give conclusion in each section.

Explain what mac address randomization is [cite, more than one].

Found several research papers and links related to mac address randomization:

Try to find a correlation between probe request (proxy of people count), which indicates unique device and number of access point [novelty] in a particular area. -> novelty

Keyword used for literature study: crowd counting wifi crowd counting bluetooth wifi probe request online database social density counting crowd android monitor mode probe request wifi people crowd density wifi bluetooth social density online data crowd sensing wifi objective social density wifi bluetooth social density data social density objective speaker count -> filtered by year, >2012

Explain why bluetooth is not a good candidate for social density estimation.

Explain that we use two proxies for estimating people count. and why do we have to bother with mac address randomization.

Found several research papers and links related to mac address randomization:

Explain about possible sensors in mobile phone.

It is known that getting the ground truth of crowd count with high precision is difficult in public places.

2.1 VIDEO BASED CROWD COUNTING

2.2 MAC ADDRESS BASED CROWD COUNTING

2.2.1 *WiFi*

2.2.2 *Bluetooth*

2.3 OTHER CROWD COUNTING APPROACH

2.4 SPEAKER COUNTING METHOD

The method of estimating social density is often referred as speaker counting. Speaker count estimates the number of people who participate in a conversation [cite].

The authors also provide the source code for crowd detection[1]

Also explains about MFCC.

The methods only work with speaker not more than 4, while in the real situation, the speaker would be more than just 4 people. Furthermore, the conversation is not a similar kind of telephony.

This topic refers to speaker clustering topic.

However, to the best of my knowledge, there is no optimal algorithm for counting number of people or speaker count. Thus, I implement different method of working.

Mention about speaker count.

Furthermore, no *a priori* information of speakers available, making it impossible to apply this method.

Video processing has limitations such as weather conditions, illumination changes, limited viewing angle, and density and brightness problem.

GSM location has an issue with privacy[2].

MAC is only a proxy since it does not infer directly to personal information, such as name or contact.

Explain what is the effect of randomized mac address [cite].

Furthermore, [6] alleges that the existence of social relationships is possible to be uncovered by using WiFi probe signals.Laptops are used to sense the data. Could uncover social links between people. Two or more users sharing one or more SSIDs in the Preferred Network List (PNL) intuitively provide some information about the existence of social relationship between them, which might be family or house mate. Affiliation network is used to construct the graph. Adamic-adar similarity: if two users share same pub and office->social link. Same Home-> social link. Demographic factor is also investigated, especially in SSID languages. This method is possibly not applicable in mobile phone, as it uses `tshark` application in laptops.

1 https://github.com/lendlice/crowdpp

This method requires preinstalled method to be existed. This method works everywhere, as long as WiFi signals are possible to be captured. This method is already tested on large scale events, such as national events, international events, city-wide probes, train station, and university, within three months of experiment. The experiment results a large dataset of log files (11M probes from 160K different smartphones). Data is stored locally for further analysis. The authors combine the networks referred from the probes to location based data, such as wigle.net. However, this method is not really possible to be implemented in smartphone. It uses IEEE Public OUI. Wifi probes are used as a new lens to look at crowd and uncover important information.

Human queue is also possible to be monitored using WiFi, as demonstrated in [33]. It is based on RSSI that is measured by a single WiFi monitor. This approach makes use of single WiFi monitor located at the queue head (service desk). The WIFi monitors collect signal traces indicated by RSSI. As the RSSI increases, the user is getting closer to the service desk. The phases are divided to 3: waiting, service period, and leaving. This method requires minimal infrastructure, which are WiFi monitors at the queue head. Existing queue monitoring approach relies on cameras or floor mats. This method works anywhere as long as a WiFi monitor exists. A laboratory experiment with 90 traces of persons has been conducted. A localized data log, i.e., data is stored locally, is used. This method has 10 secs of latency. Two fold cross validation with manually logged ground truth are used to evaluate this method. 10 secs time resolution is expected in this approach. Average error increases when the service time is 180s or more. Each queuing user is equipped with custom Android app that sends WiFi packets at 10pkt/sec.

WiFi and Bluetooth were also used to estimate crowd densities and pedestrian flows in [24]. WiFi and Bluetooth in laptops are used to sense the signals. This method could provide reliable source of ground truth for pedestrian flows with low cost of installation. The approach is divided into several methods, namely naïve (only counting MAC addresses), time (include time information), RSSI (include signal strength), and Hybrid (RSSI+Time). No ground truth for density estimation (GT only for movements). Although Bluetooth is mentioned, it is not significant in terms of results, as this method has high number of false positive. This approach utilizes two identical and synchronized laptops. The method could run anywhere as long as a WiFi monitor exists. Single realistic scenario carried out in airport during 16 days period, resulting in 11M probe request, 6600 SSIDs (public), 8.5M probe request and 4k SSIDs (security area). The data is localized in laptops. Ground truth is provided by security check in german airports. Pearson correlation: 0.75 for average in hybrid approach. 0.93 in best case. Incorporating external data sources, eg, opening time of security gate. Testing it in different scenario (places)or Different positioning. It alleges that bluetooth estimation is less accurate: 0.53 r-test in best case. Bluetooth/WiFi ratio: 4%.

A research [2] utilizes MAC address data to determine spatio-temporal movement of human in terms of space utilization. Specifically, this method leverages MAC address in Bluetooth and WiFi. This method alleges that it could track group gathering and behavioral pattern. CrossCompass by Acyclica Inc is used to capture MAC address from both BT and WiFi. Passing visitors are filtered (<4mins in 1 hr). Groups are determined when several MAC addresses enter and exit the lounge area in almost similar time. However, the assumption of groups is weak. A MAC address scanner (single) is required to perform the measurement. This method could run anywhere. Tested within three weeks, the resulting data consists of timestamp, MAC address, and RSSI, stored in 35K log lines and 418 unique devices. Centralized approach is a kind of proposed method. The central monitors MAC address spatio-temporal movements. The data is dump for 3 weeks. This approach does not a realtime result, as the analysis was carried out after 3 weeks data dump is created. The accuracy depends on how many devices are turned on. Future research is aimed to combine with camera or psychological future work: human socializing behavior assessment, human response to changes on environmental structure.

A crowd density estimation is proposed in [35], which leverages Bluetooth in smartphone. The crowd density is quantized into 7 groups, ranging from nearly empty to extremely high (crowded), which will be the feature in the training phase. The experiments were set up for 3 times, with 4 hours of duration each. 10 students were recruited to carry out the experiments. Six features of scanning were developed to increase the accuracy of estimating the crowd. Volunteers are equipped with scanning mobile phone that scans nearby Bluetooth signals. This method is not suitable for single mobile phone implementation, as it requires n>10. No prior infrastructure is needed. Cameras are used for ground truth checking. This method works everywhere. An experiment is carried out to test the method on a final soccer match in a football stadium. The data stored locally for further processing. No real-time result. This method achieves 75% accuracy.

Bluetooth data is also used to analyze spatio-temporal movements of visitors event in Belgium [31]. Large datasets were extracted during the experiments. This approach works with 22 Bluetooth scanners were placed around the festival area. Combination of class 1 (larger area) and class 2 (smaller area) were used. Data preprocessing used to compress the logs and to infer direction of visitors (in/out/pass). GisMo (geoggraphical movements) is also used. major and minor address are used to distinguish BT device type (phone or car handsfree, etc). This method lacks in the biased results between sensed

BT and real people count. Only BT scanner installations are required to conduct this approach. Outdoor is the preferred location to run this method. Tested in Ghent festives, 10 days event with 1.5M visitors. Custom bluetooth scanner is used. Two bluetooth class (1 and 2) were used to capture the packets with different area. As this approach does not come with real time result, the analysis were carried out after the huge data dump (260M lines) is created. The ground truth is provided only by comparison with official visitors count. 11% is the ratio of sensed MAC addresses and real populations. More behavioral analysis of the visitors. No technical future research direction. The detected MAC is a ratio with real values.

Bluetooth, again is proven to be a potential source of tracking socially contextual behavior, as seen in [7]. Using Bluetooth trace, Chen, et. al. have shown the result with 85.8% accuracy. A BT feature based classification model is constructed, 6 representation are: working indoors, walking outdoors, taking subway, go shopping in the mall, dining in the restaurant, watching movie in cinema. A user ran the experiment during the day, and a questionnaire for ground truth are asked at the end of the day. C4.5 Decision Tree and 10-folds cross validation are utilized as evaluation. However, this approach have a drawback, because if the user set the Bluetooth off, this approach would be useless. This method works on outdoor. This work involved 3 volunteers, with 1-2 weeks of BT traces. The data is logged in user's smartphone. This is a moving approach, as it is implemented in users phone. At the end of the day, the user recalls and labels their contextual behavior using questionnaire. The future work is directed to increasing the accuracy, especially when Bluetooth signals are detected sparsely. Furthermore, fusion of RF signals: GPS, GSM, WiFi as well.

Movements pattern and landmark preferences are possible to be extracted from publicly available photo repositories, such as Flicker and Panoramio, as presented in [15]. Analyzing publicly available photos repository, such as Flicker and Panoramio, and extract geotagged photo information which provides coordinates of location and time of taking the photos.

A work [1] alleges that WiFi prevails Bluetooth in several criteria. Firsly, Bluetooth requires longer time to discover. More than 90% of detected MAC address were WiFi MAC address. MAC is unique address for most IEEE 802 technologies.

A combination of WiFi fingeprinting and Pedestrian Dead Reckoning (PDR) are used to monitor Indoor environment by means of crowdsourcing [23]. This method requires predeployed WiFi accesspoints in the area. This method, which works in indoor location, Ekahau mobile survey is used as the ground truth source. In the future, the works are aimed at evaluation with longer period and fusion with other RF signals. The result is similar result with state of the art WiFi survey tools.

An interesting insight is found in [5], as this research goal and method are really similar with our research in passive behavioral monitoring.This method monitors social interaction using Wifi, Bluetooth, audio, and interactions on the phone for ambulatory monitoring. Audio, radio, and phone interaction data are processed differently. Unsupervised clustering is used to count the person in a conversation. Subjects location is determined using GPS and WiFi Mac address. Nearby Bluetooth devices and devices within the same WiFi network are used as indicators of social interaction. Subjects activity in messaging apps are monitored, notifications are logged. The data are aggregated in certain time interval, eg., a week, for later analysis. Unsupervised clustering on microphone data to count the person that participate in a conversation. Audio based monitoring is not yet completed, however. This method requires no prior installation on infrastructure and works both outdoor and indoor. The method is localized within the smartphone. No realtime analysis is performed, as the data is dumped, and latter analysis is performed. No reliable ground truth is mentioned in the paper. 76% accuracy for phone interaction is achieved.

A research [19] is also a little bit similar with the Paul's research, which tries to determine social Well being. This method uses contacts, phone calls, text messages, GPS and WiFi (location), BT proximity, and social app usages from the monitored patients. Multimodal interaction is used, such as phone calls, SMS, location (GPS+WiFi), Bluetooth proximity, social app usages. The contacts are labeled on groups (friend, colleague, family, etc). In the other way, contact classification, place detection, proximity analysis, and application usage. Bluetooth is used only detecting the type of nearby device, salesman actively meets clients while developer tends to stay in the office with the team members nearby. Frequency and time are used for social application monitoring. Personal communication score is also devised. DBSCAN algorithm is used in this approach. This method does not require any pre installed infrastructure. This method works well in outdoor, as at indoor location GPS does not work. 106 mobile users, 107 days of data on average, 68, 529 phone calls, 20k SMS, nearly 10k labeled contacts No realtime result in this research, as the app saves log files, and periodically sent to server. The ground truth information is gained from labeling in user's contacts. The future works are directed to comparison of several social well being status of people in the same demography. Adding ambient noise detection (audio data).

A work [37] tried to count the crowd using CSI, which is proven to have a monotonic relation with the number of moving people. The result seems promising, although some errors are observed.

A more energy efficient method to exploit sensor in smartphone is presented in [18]. It makes use of, what they called, *Smartphone*

App Opportunities. The approach is named Piggyback Crowd Sensing (PCS).

Bluetooth has again proven to be one reliable method to estimate crowd density [34]. The work alleges that it could even reach 82% accuracy in the best case.

[22] describes the possibility to use ZigBee to estimate crowd density by measuring the RSSI and LQI. This approach requires prior infrastructure.

More approach on WSN is described in [41]. With similar solution in [22], [41] employs more WSN. It has normal and large-scale experiment.

[32] explains the possibility of tracking people movement and contact by using bluetooth and wifi.

Another point of view to track pedestrian flocks is presented in [17]. It uses WiFi signals with 3 different features to infer the flocks.

A paper [3] presented a method that combine geo-fencing with coarse WiFi localization for building evacuation.

An example of crowd monitoring is presented in [20], where it is implemented for Hajj in Mecca, Saudi Arabia. It utilizes RFID tags along with a specialized app for monitoring the pilgrims.

A good experiment that tried to find the correlation with WiFi probe-request counts and real people counts is presented in [39]. It employs wifi monitor mode and manual people counting by using tally counter.

[25] evaluates crowd counting using WiFi probe-request signal. The result showed that this is possible, although achieved not in really high accuracy.

A combination with Drones for people counting is presented in [30]. [29] presents a brief explanation about the method in indoor measurement. However, no ground truth explanation is present.

Audio tones are also proven to be a good potential method to infer crowd count [16]. However, in this method every tracked phone must be pre-installed with the audio tone generating app. Thus, this method is unable to track phones which are not pre-installed with the app.

[9] presents crowd counting method that leverages single WiFi transmitter and receiver. This method does not require prior data training, which makes this method novel.

RSSI is used to infer people count in a controlled environment, as presnted in [40].

Smartphone trajectories are tracked using captured WiFi signals in [21]. The error is up to 70 meters compared to the GPS ground truth.

[36] has showed successfully how to implement WiFi RSSI as a way to track smartphone trajectories. The result showed that it is promising, having only 70 meters error from GPS ground truth.

[8] presents the method to detect occupancy and count the people using WiFi power only.

3 EXPERIMENTAL SETUP

In this chapter we present the method of the experiments to collect the data. We first start with the investigation of Media Access Control (MAC) address randomization behavior. Then we discuss the main experiment, which is about examining the correlation between the level of social density and smartphone sensor readings. Lastly, we present the method of data extraction from collection of raw log files.

3.1 MAC ADDRESS RANDOMIZATION

In this first setup we are interested in seeing the behavior of MAC address randomization, observed in both Android and iOS devices [10]. By using this randomization technique, the devices will randomize its MAC address in each particular circumstances to increase the privacy of the user and thus making the current people tracking technology no longer works [28]. We need to investigate MAC address randomization behavior because we will use the MAC address counting as a proxy to estimate the level of social density. MAC address randomization is a potential threat to this approach.

In this experiment, we exploit the active scanning mechanism of WiFi, in which each WiFi-enabled device is required to broadcast probe request packets to scan for available WiFi AP [14]. In the probe request, a piece of unique information exists, e.g., the device's MAC address and supported WiFi modes, which indicates where the probe request packet comes from. We capture the probe request packets from nearby WiFi-enabled devices and store the captured information to a log file.

The randomized MAC address uses locally administered address, which is indicated by the second-least-significant bit of the first octet of the address [14]. The original MAC address uses universally administered address, which is uniquely assigned by its manufacturer.

In this experiment we take note on **a)** the timing when the randomized MAC address appears, **b)** the Sequence Number (SN) field[1] of the packet, **c)** and the variation of the MAC address.

We investigate the randomization behavior in both iOS, using iPad mini with iOS 10.0, and Android, with LG Nexus 5X with Android 6.0 (Marshmallow). When experimenting on iPad mini, we turn the LG Nexus 5X off, and vice versa, to make sure that each device is not

1 The SN field is a 12-bit field indicating the sequence number of a probe request packet. This marks the order of how the packets are broadcasted.

disturbing each other. We do this experiment within 30 minutes for each device.

We choose a remote area where we cannot detect any other probe request except from our device to perform the experiment. We use Wireshark[2], a popular network protocol analyzer software, to capture and store the captured probe request packets to a `pcap` file. We run this experiment on Apple's MacBook Air with built-in WiFi card that supports monitor mode.

3.2 CORRELATION BETWEEN CROWD COUNT AND SENSOR READINGS

In this experiment we are interested to see the correlation between the number of people in the surroundings and the sensor readings. We collect the data in different conditions to see the trend of the correlation. Correlation between smartphone sensor readings and people count indicates that smartphone sensor readings are possible means to estimate the level of social density in the surroundings. However, we have to be aware of the strength of the correlation. We are also interested to see the trend of the variables, i.e., is it negative or positive correlation.

In this section we start with the method we use to count or estimate the crowd count. Then we specify the smartphone sensors that we use in this experiment and their corresponding outcomes. We discuss the different location and timing setup of this experiment as well. Lastly, we finalize with a detailed description about technical scanning mechanism.

3.2.1 *Crowd Count Estimation*

We use two approach to estimate the crowd count in the surroundings, by using manual counting on photographic images and unique MAC address counting from captured probe request. We are estimating the crowd count rather than getting the real precise ground truth because it is known that getting the ground truth of crowd density in public spaces is difficult [34]. In the end we will compare the sensor readings with these two crowd count estimation.

3.2.1.1 *Probe Request Based Estimation*

Probe request is a data packet broadcast by WiFi-enabled devices to scan for available AP. This mechanism is part of active scanning in WiFi standards [14], which is more energy efficient than passive scanning. We decide to implement unique MAC address counting in probe request as it is proven to be a promising method to estimate

2 https://www.wireshark.org

crowd count [39]. During the experiments, we capture the probe request packets from nearby devices and take note on the unique MAC addresses. Counting the unique MAC address will result in a list of unique device in the surroundings.

In this experiment we capture the probe request packets in WiFi channel 1 (2.4 GHz). We are not capturing packets in other WiFi channels as WiFi-enabled device will broadcast the probe requests to all available WiFi channels [14]. Furthermore, capturing packets in every WiFi channels is not doable in a single device due to the limitation of a device that is only able to be in a certain WiFi channel at a time. Capturing packets in multiple channel requires channel hopping, i.e., hopping from one channel to another within a short time interval, which is considered a lossy method and prone to losing some probe request packets.

Although probe request based estimation is promising, some drawbacks are also present. In this method, we are not able to distinguish the type of devices, i.e., whether it is a smartphone, tablets, or computers. Although recently one usually brings a smartphone [39], which means we can deduce that a smartphone means a person present, there is also a possibility that one brings more devices or no devices at all.

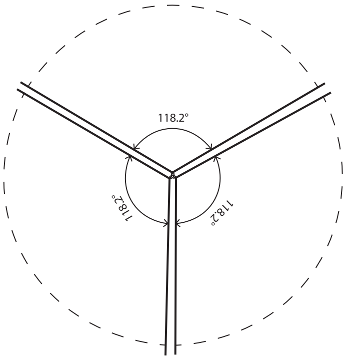
3.2.1.2 *Manual Counting Using Photographic Images*

In addition to probe request based estimation, we incorporate another crowd counting estimation method using photographic images. We consider this method as an estimation rather than ground truth as photographic images are subject to light and sight, i.e., physical obstacle would interfere the final result. Compared to the probe request based estimation, this method could not detect people through walls or buildings and thus does not really represent the actual condition of the location. However, we consider this method to be closer to the ground truth.

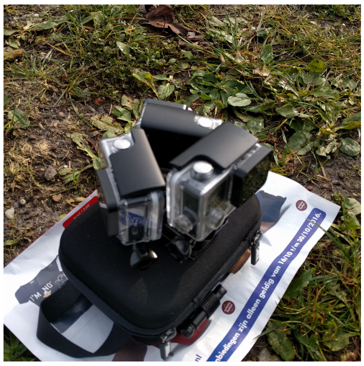
Several options in image based manual crowd counting exist. However, a mechanism that supports wide FOV, i.e., able to cover 360 degrees of horizontal FOV, is preferred. Some of the options that we consider are panoramic photograph and wide-angle photograph. During our early testing, panoramic photograph using smartphone suffers from misaligned images, as panoramic photograph is a computer-based concatenated images taken in different timestamp. This causes some object could appear more than once, or even completely disappear. Thus, we decided to use wide-angle photograph to achieve 360 degrees of horizontal FOV.

We use GoPro[3] Hero4 silver wide-angle action camera to get the photographic image. According to GoPro technical specifications [27],

3 https://gopro.com



(a) illustration



(b) implementation

Figure 1: GoPro arrangement to achieve 360 degrees of horizontal FOV.

its maximum horizontal FOV is 118.2 degrees in 16x9 wide mode with 17.2mm focal length. Thus, to achieve 360 degrees of FOV we use three GoPro cameras positioned in circular arrangement, as depicted in Figure 1. Although some blind spots are still present, this setup is still able to capture objects within intended range.

We employ time-lapse photography technique to capture the surroundings in preference to normal video capture. In this technique we capture a still image in each five seconds, resulting 12 still images in each minute. We do not employ video recording to conserve GoPro battery. As stated in GoPro technical specification of battery life [26], estimated battery life of taking video is roughly two hours, while our experiment is planned to be more than two hours (plus back-up time). We consider changing battery during data collection is impractical. Moreover, taking time-lapse images would increasingly save more data storage.

In the end, we manually do head counting based on captured images grouped in each time interval. We make sure that one person is counted once to avoid counting the same person multiple times.

3.2.2 *Smartphone Sensor Utilization*

We only use WiFi and microphone as sensors because those sensors are able to perceive the surroundings no matter how the smartphone is operated and positioned. This means that the passive monitoring process can still running in background regardless how user use the smartphone. In the other hand, camera based approach requires the smartphone to be positioned accordingly to be able to capture appropriate images for crowd counting.

3.2.2.1 *WiFi scanning*

Ideally we use probe request based crowd estimation, as discussed in Section 3.2.1.1, directly in the smartphone. However, this is not possible due to restriction in the mobile operating system. Probe request based estimation only works in WiFi monitor mode [28, 40] and monitor mode is only accessible if the smartphone is rooted, jailbroken, or installed in custom Read Only Memory (ROM), which is considered as illegal in most countries [12].

Hence, we count the available AP nearby and observe its signal strength in place of unique MAC address counting in probe request packets. We take note of AP's Basic Service Set Identifier (BSSID), which is unique and based on MAC address. We are not particularly interested in AP's Service Set Identifier (SSID) because there might be multiple APs with the same SSID. We measure the signal strength of the AP in RSSI.

3.2.2.2 *Ambient Noise Recording*

In addition to WiFi scanning we also record the ambient noise to perceive nearby condition. We assume that more crowded locations will have high ambient noise, while less crowded locations will have low ambient noise. We measure the ambient noise in decibels (dB). Moreover, we implement speaker count algorithm based on unsupervised learning method proposed by Xu et al [38]. This approach will estimate how many persons are speaking in the audio recording.

3.2.3 *Location and Timing*

To obtain wide range of data, we select four different locations that represent low and high crowd density as well as indoor and outdoor location. We plan to do our experiment where WiFi AP use is not restricted, i.e., people are free to set up their own WiFi AP in anyway they prefer. Some locations where the use of WiFi is restricted exist, for instance, University of Groningen complex. In the university complex, `eduroam` is the only the official available AP and the occupants are discouraged to install their own AP. Thus, making this not suitable for our research. Table 1 summarizes our location selection.

To save GoPro battery, we select 30 minutes as the scanning duration in each location. As we are picking four different locations, this would sum up to two hours of image capture. We also select daytime as the preferred scanning time because that is the time when most crowd are observable.

Speaking of the location selection, remote area is a far-off outdoor location located in Paddepoelsterweg, Groningen. The surroundings are mostly trees and grasses. No visible buildings or dwellings exist but there is only a narrow asphalt pathway where sometimes people

Table 1: Summary of location and selection for the experiment

Location	Type	Crowd Level	Scanning Time
Remote area	outdoor	low	11:00-11:30
Home	indoor	low–medium	08:15-08:45
Paddepoel shopping center	indoor	medium–high	14:45-15:15
Grote markt	outdoor	high	12:00-12:30

or vehicles pass by. Approximately no more than 5 individuals are present at the same time. We carry out the experiment in this area during daytime, from 11:00 to 11:30.

Aside from the remote area where the crowd is less likely to be observed, we conduct a data collection at home during breakfast time, from 08:15 to 08:45. This indoor location is located at Planetenlaan 264, Groningen. Currently, there are only 6 inhabitants living in the house. However, people sometimes pass by in front of the house and they might influence the measurement result.

Padeppoel shopping center is an indoor shopping center located in Paddepoel district, Groningen. The shopping center, which is 14.920 m^2 in size, holds around 90 shops [4]. According to statistics [4], it has approximately 90.000 visitors per week. We perform the experiment during the peak hours, which is from 14:45 to 15:15.

Grote markt is a open city square which is located in the center of Groningen city. This location is able to hold roughly 8000 visitors at the same time, according to the official government statement [11]. We are planning to do data collection in Grote Markt around mid day, from 12:00 to 12:30.

To see the variance between days, we plan to do the experiment in four days, ranging from weekdays to weekend. We start the experiment in Wednesday and finish it in Saturday. We stick to the same schedule for each location.

3.2.4 *Scanning Mechanism*

In summary, we are using three inputs to collect and to perceive the surroundings, namely WiFi, microphone, and wide-angle camera. The data collection process is split into several small cycles of x minutes to avoid biased result caused by randomized MAC address. The x will be determined by the MAC address randomization experiment described in Section 3.1. We keep repeating the cycle until we reach 30 minutes. Figure 2 depicts the description of each cycle.

As depicted in Figure 2, we work with WiFi to capture the probe request and count the number of available AP. We cannot perform these tasks simultaneously, because capturing probe request must be

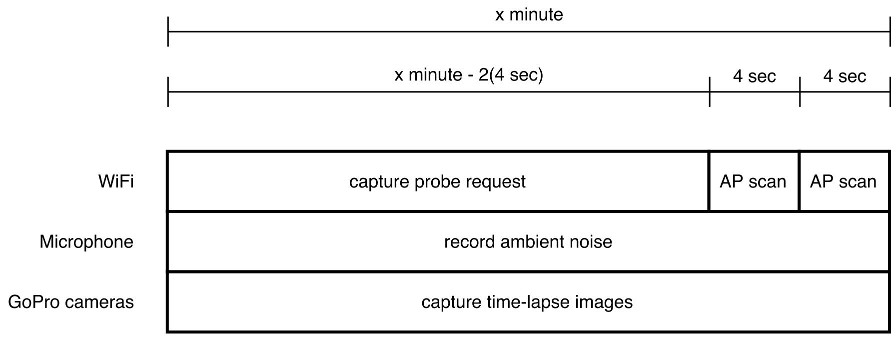


Figure 2: Sensor measurement in each cycle.

carried out in the WiFi monitor mode. Monitor mode is one of the seven modes, namely master (acting as an AP), managed (acting as a WiFi client), ad-hoc, mesh, repeater, and promiscuous, that 802.11 WiFi cards can operate in [14]. Being in monitor mode, the WiFi card is disconnected from any wireless networks. Thus, we decide to firstly capture probe request before counting the available AP. We count the available AP twice to achieve better stability. Both microphone and GoPro cameras continuously recording ambient noise and capturing time-lapse images in each cycle.

We use Apple MacBook Air, with built-in WiFi card and microphone, as a WiFi scanning and audio recording device. To capture probe request, we use `tcpdump`[4], a free packet analyzer that runs under the command line, and we use console based Apple's AirPort utility, a software designed by Apple to manage WiFi network, to count available access point. The output of probe request capture is `.pcap` file, a standard file for capturing network traffic. AP counting results in plain text files. We work with console based audio editing software, Sound Exchange[5], to record the ambient noise to `.wav` file format.

To automate the WiFi scanning and audio recording process, we write a bash script[6]. We label the resulting log files in the corresponding timestamp and location. Our code is publicly available online[7].

3.2.4.1 *Effect of Scanning Time*

In addition to the previous experiment which is particularly aimed to see the variance between days, we also conduct an experiment aiming at seeing the variance between scanning time. In this experiment we select Grote Markt Groningen as the scanning location with four different scanning time, taken at **a)** 09:00, **b)** 12:00, **c)** 15:00, **d)** and

4 `http://www.tcpdump.org`
5 `http://sox.sourceforge.net`
6 Bash script is a list of Bash commands that run on console based application to execute particular tasks.
7 `https://github.com/gtrdp/masters-thesis-guntur`

Table 2: Smartphone sensor readings and the extracted parameters

Sensor	File format	Extracted parameter	Extraction method
WiFi	`.pcap`	unique MAC addresses	text processing
WiFi	`.txt`	AP signal strength	text processing
WiFi	`.txt`	AP count	text processing
Microphone	`.wav`	speaker count	machine learning
Microphone	`.wav`	peak level	audio processing
Microphone	`.wav`	root mean square	audio processing
GoPro cameras	`.jpg`	head count	manual counting

18:00, in the same day. The rest of the experimental setup of this process remains the same as previous experiment. However, we do not employ GoPro time-lapse image capture.

3.3 DATA EXTRACTION

The experiments mentioned previously will produce different formats of hundreds of raw files that need further processing to give us more insights. The files are, namely, `.txt` for AP list, `.pcap` for captured probe request packets, `.wav` for recorded ambient noise, and `.jpeg` for time-lapse images. Each file format needs different treatment to extract the data. Table 2 summarizes all sensor readings and the extracted parameters.

3.3.1 *WiFi Raw Data Extraction*

The WiFi based data collection result consists of two types of file, namely `.txt` file for AP list from AirPort sensing, and `.pcap` file for captured probe request packets from `tcpdump` sensing. As shown in Table 2, we extract the number of available AP and the mean of AP's signal strength from this file, while the number of unique device is derived from the `.pcap` file. Each cycle produces two individual `.txt` and `.pcap` labeled in its corresponding timestamp.

Figure 3 and 4 display the example of sensed AP list and captured probe request respectively. From the AP list depicted in Figure 3 we are interested in BSSID column and RSSI column to count the AP and measure the signal strength. From the captured probe request packets, as depicted in Figure 4, we take note on the Source Address (SA). We develop a text processing program written in Python script to extract preferred elements. We plot the result to scatter plot using `matplotlib` package in Python [13].

```
             SSID BSSID             RSSI CHANNEL
            Ziggo 6c:aa:b3:27:72:ac -84  140
            Ziggo 6c:aa:b3:26:af:bc -87  140
     Ziggo22211-5G 0c:54:a5:b8:25:e8 -84  136,-1
          eduroam c4:10:8a:60:d4:7c -84  132,+1
Draadloos Groningen c4:10:8a:20:d4:7c -84  132,+1
     Ziggo21616-5G 60:02:92:11:4d:e6 -87  128,-1
            Ziggo 6c:aa:b3:26:af:0c -86  116,+1
          OneTeam e2:55:6d:20:30:96 -85  108,+1
  WEEKDAY Free WiFi e2:55:6d:20:30:92 -85  108,+1
```

Figure 3: Example of AP list.

```
BSSID:ff:ff:ff:ff:ff:ff DA:ff:ff:ff:ff:ff:ff SA:ec:1f:72:10:44:01
BSSID:ff:ff:ff:ff:ff:ff DA:ff:ff:ff:ff:ff:ff SA:0a:0f:c6:e5:e0:cb
BSSID:ff:ff:ff:ff:ff:ff DA:ff:ff:ff:ff:ff:ff SA:2e:60:57:70:d3:eb
```

Figure 4: A fragment of captured probe request packet.

3.3.2 *Recorded Ambient Noise Extraction*

We extract single ambient noise recording `.wav` file to three independent measurements, namely the Peak Level (PKLV), Root Mean Square (RMS), and speaker count. We use the same audio processing program as ambient noise recording process, namely Sound Exchange, to extract the PKLV and RMS from the `.wav` file, while we use unsupervised learning method proposed by Xu et al. [38], namely Crowd++, to infer the number of speaker count.

The PKLV is the highest value of a total waveform, while RMS is the effective value or the mean. The PKLV and RMS are both measured in decibels (dB). As a performance test of Crowd++, we perform speaker count check in several audio recordings with known ground truth. The recordings are a commencement speech (1 speaker), pop duets (2 speakers), and acapella (5 speakers). We will use the result as a consideration whether this speaker method is reliable.

3.3.3 *Manual Head Counting*

We firstly collect all time-lapse images taken in different location from the three GoPro cameras. Then, we group each time-lapse image separately to the corresponding cycle and camera. We then manually do head counting based on those images and apply pattern recognition (manually) to avoid counting the same object that appears more than once multiple times. The result is a total head count of a cycle per location.

This chapter presents the method that we plan to execute the experiments, started by MAC address randomization investigation, then followed by an examination of the correlation between the people count and the smartphone sensor readings, and ended with how we extract the data from the raw log files. The next chapter will tell us the result of each experiment.

4 RESULTS

In the previous chapter, we present the bla bla In this chapter

Explain about the data extraction.

Mention all experiment setup. - randomization - wifi - in days - in time

Display the final result, using table

Remember to explain the randomization result.

Ground truth: show an example of low density and high density crowd, comparing the 4 locations.

Interesting finding: nexus 5x immediately sends out probe request when wake up from sleep.

Randomization results indicate that 1 minute is the preferred time.

Randomization Experiment result:Experiment result: The phone immediately sends out probe request with original mac when it wakes up from sleep. Usually 4 or 10. If the phone has woken up from a long sleep, more than 1 minutes. When the screen is locked. The phone keeps sending out using the same first 3 byte of address. Brutally changes the last 3 octets. The SN is close, but not really sequential. iPad: also keeps sending out probe request when the display is on. Take note the changes of mac address of LG Nexus 5X. Every 10 secs (roughly) sends out 2 probe request, same manufacturer, different last 3 octets. Sequential or close SN. But when it is stable, it sends out every roughly 60 secs, with each different mac (but same). Count of probe beacon: 1 or 2, or even 3. To prove it, I turned off the phone and there is no such mac address. The mac address SN is close, but not sequential. The pattern: original -> 10 sec -> 4 times random -> 60 secs. The SN is restarted when the phone is active (not sleeping). The randomized MAC address: da:a1:19. And LG is always using that same mac? For the next experiment, please make sure that your phone WiFi is switched off. When the screen is on, the phone does not send out randomized mac address. Also test it using tcpdump. When the phone restarted, it firstly sends out real mac address. Create flowchart to filter out randomized mac. Every burst of probe request, the address changes. Even when WiFi is off, LG occasinally sends out probe request with original mac.

Experiment result iPad: The iPad keeps sending out randomized mac even tough the screen is on. Then the loading ion appears, the burst of probe request also captured. Then iPad wakes from sleep, the mac address also changes. But still randomized. When the screen is on, it keeps sending out probe request within 3, to 10 secs. Take notes the randomized mac addess. Take notes the setting of ipad prior and after sim card installation. When I switched off the WiFi and on, the mac address changes. The SN is also restarted. No difference, when the sim card is installed or not. When ipad is connected to an AP (ad hoc, from Nexus), it sends out original mac address. But the SN is always restarted. (Chance of solution) If the iPad is in sleep mode, it sends out roughly every 2 minutes (135 secs) or even 4 minutes. and the SN is always restarted. The SN is always resetted in each burst. The pattern, 2x2 minutes, 4 minutes, then change MAC address

Signal strength: more than 40dB SNR = Excellent signal (5 bars); always associated; lightening fast. 25dB to 40dB SNR = Very good signal (3 - 4 bars); always associated; very fast. 15dB to 25dB SNR = Low signal (2 bars); always associated; usually fast. 10dB - 15dB SNR = Very low signal (1 bar); mostly associated; mostly slow. 5dB to 10dB SNR = No signal; not associated; no go.

Explain by conclusion, not using whole data effect of day effect of location effect of scanning time put it in a whole picture signal strength: WiFi and probe request

Working on decibels. Important, writing: also address the microphone sensitivity. Sound level decreases by 6dB with each doubling of distance from the source. The sound is already using ambient noise reduction. Those microphones are attuned to a specific (and rather narrow) range of sound intensity.

Writing: present the scatter data with colors.

Presenting: use the graph of prediction error to estimate the error. also for cross validation.

Possible graph:

- Number of removed mac address
- number of walking people
- available ap vs unique device
- count of manufacturers comparison
- final scatter data
- number of scanned probe per device.
- number of people entering and leaving the area.
- time vs count of unique devices
- time vs count of access points
- unique devices vs access points
- randomized mac addresses count

Question: Does weather affect WiFi performance?

Possible research: generate separate graph that explain one location with different time window: using scatter plot.

Explain the features on the data.

Make the datasets available online.

Devote a section only to show the mac address randomization result.

Explain the result in percentage as well, instead of manual count.

Writing: 1 minute is selected to minimize the effect of MAC address randomization, as well as according to our experiment, 1 minute is the interval of sending probe request in several manufacturers (it subjects to change) assumption when it sees cars or buses sound depends when the people speak out or not the setting may vary in cities or even countries. explain why dont we use channel hopping scanning.

Make sure that the data is available publicly, mention the url.

show the graph of Phone manufacturer and the graph of show the graph of scanned device (comparison between laptops, smartphones, and other)

Explain the density of each location in bar chart, comparing both head count and probe request count.

explain the size of data dump (images (MB) and text (lines))

Use table of simulation about randomized mac address using different time window.

show the correlation graph per day per location, then combined per day, then combined all location all day

go for detail first, then combine all measurement using correlation graph matrix

an object may appear more than once in the manual camera: we used pattern recognition to avoid multiple counting.

other probe request from other device may be captured during mac address randomization experiment.

5 REGRESSION MODEL AND DISCUSSION

Explain about the previous chapter, begin with a good starting point of a chapter.

Explain the limitations of the thesis. Where and how the method works best.

present the result of each location. and compare within days present the result in grotemarkt, and explain the difference between time of scanning.

Explain that using classification might give better accuracy that regression.

Also give graph of MAC address manufacturer.

Explain using bar chard about the comaprison of maximum unique device and head count: average, in each day. Also apply this for timely related

Use wigle to explain that this could not be generalized. Mention comparison of one place and another place. in other cities or contries.

Mention about VAD and explain why it is not applicable.

Explain that this method does not work in restricted environment, such as university location.

Looking for microphone recording in phone.

Possible research using dB (decibels) to identify social density. Decibels does not correlate linearly, but rather logaritmically. -> altought it turned out that it is not really good, ie., it does not have a good correlation.

0.3 of correlation means that 30

explain that the IE method is not really 100

Argument, writing: it is hard to count people inside the bus. we rely on an assumption that says everyone brings their own mobilephone with them, thus we can track it, just like what retail companies do. To avoid randomized mac, we use discretize the monitoring, instead of doing it continuously for a long time, we did it in separate scanning interval. Why dont you use 2 devices for separate purpose? one for probe request and one for access point. Limitation: This work is only limited to free neighbourhood, i.e., this does not apply to a wifi restricted location such as university buildings.

Important, writing: also address the microphone sensitivity.

Working on decibels. Important, writing: also address the microphone sensitivity. Sound level decreases by 6dB with each doubling of distance from the source. The sound is already using ambient noise reduction. Those microphones are attuned to a specific (and rather narrow) range of sound intensity.

cross validation is used to validate the mode, explain a little bit

quantitative, continuous result: regression classes, discrete result: classification

Explain that I used R to do data analysis. Also mention what packages are used for each model, as a summary, better to draw a table about all classes used.

Explain a little bit about 10 folds cross validation.

Mention eps-regression and nu-regression in SVM

sections: - linear model - non linear model

5.1 DISCUSSIONS

Possible explanation: explain that the number of access point might increase in a crowd because of the ad hoc access point. also use We expect that this affect the ap count, but it turned out that it does not.

Turns out that multiple APs are using the same eduroam as their SSID, however, they have different MAC addresses. -> explain as a fact.

When android is in energy saving mode, the OS prohibits any app for doing WiFi Scan or any other scan.

[Possible problem] A drawback of scanning WiFi probe request: people located in other room (not within the person's eyesight) is still detectable, thus, worsen the results. Combine with sound Combine with GPS location if there is no sound detected.

Counting people using wifi has an issue: it can detect people through the walls, which people don't see. what do you think?

Explain that this method does not work in restricted environment, such as university location. Writing: explain why we do not do that in school/university, because WiFi is highly restricted in campus, i.e., we are not allowed to have individual access point in school.

We also select daytime as the preferred scanning time because that is the time when most crowd are observable. This implies that our collected data resemble only daytime duration, meaning that conclusion might only be able to deduct for daytime.

6 CONCLUSION AND FUTURE WORK

In the future work, we are interested in working more closely with estimating social density. Regression model based on the data to get the count of people. Machine learning method is also interesting to be implemented.

To the best of our knowledge, there is no approach that tries to combine or fusion several sensor measurements. Furthermore, no prior investigation of crowd counting using smartphone has been proposed, as mainly approaches are leveraging dedicated sensing devices.

mention the important message, that wifi could be use topredict roughly social density. but to generalize we must get more data.

This research is trying to bla bla.

Future work, examine the correlation between ap count and location. future work, examine the solutino of mac address randomization using probe request data.

VAD might be a good candidate to detect whether there is a person speaking or not.

The result will be useful for BeHapp aplication [cite sociability]

Explain the limitation of the study.

use VAD

Explain that this method does not work in restricted environment, such as university location.

A

APPENDIX TEST

Lorem ipsum at nusquam appellantur his, ut eos erant homero concludaturque. Albucius appellantur deterruisset id eam, vivendum partiendo dissentiet ei ius. Vis melius facilisis ea, sea id convenire referrentur, takimata adolescens ex duo. Ei harum argumentum per. Eam vidit exerci appetere ad, ut vel zzril intellegam interpretaris.

More dummy text.

A.1 APPENDIX SECTION TEST

Test: Table 3 (This reference should have a lowercase, small caps A if the option `floatperchapter` is activated, just as in the table itself → however, this does not work at the moment.)

LABITUR BONORUM PRI NO	QUE VISTA	HUMAN
fastidii ea ius	germano	demonstratea
suscipit instructior	titulo	personas
quaestio philosophia	facto	demonstrated

Table 3: Autem usu id.

A.2 ANOTHER APPENDIX SECTION TEST

Equidem detraxit cu nam, vix eu delenit periculis. Eos ut vero constituto, no vidit propriae complectitur sea. Diceret nonummy in has, no qui eligendi recteque consetetur. Mel eu dictas suscipiantur, et sed placerat oporteat. At ipsum electram mei, ad aeque atomorum mea. There is also a useless Pascal listing below: Listing 1.

Listing 1: A floating example (`listings` manual)

```
for i:=maxint downto 0 do
begin
{ do nothing }
end;
```

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