Extracting Localised Mobile Activity Patterns from Cumulative Mobile Spectrum RSSI

John Doyle*, Ronan Farrell, Seán McLoone, Tim McCarthy, Peter Hung
Institute of Microelectronics and Wireless Systems,
National University of Ireland Maynooth,
Maynooth, Co. Kildare,
Ireland
Email: *jcdoyle@eeng.nuim.ie

***Abstract*—Techniques for observing the flow of people are creating new means for observing the dynamics between people and the environments they pass through. This ubiquitous connectivity can be observed and interpreted in real-time, through mobile device activity patterns. Recent research into urban analysis through the use of mobile device usage statistics has presented a need for the collection of this data independently from mobile network operators. In this paper we demonstrate that by extracting cumulative received signal strength indication (RSSI) for overall mobile device transmissions, such information can be obtained independently from network operators. We present preliminary results and suggest future applications for which this collection method may be used.**

***Index Terms*—RSSI, Erlang, human monitoring, geo-temporal weighting.**

I. Introduction

Mapping applications which present the flow of human activities are now becoming increasingly common, one of the main contributions to this is the vast amounts of information made available from mobile devices. In 2007 the number of mobile phones in Ireland numbered 5.3 million [1] while the human population numbered 4.3 million [2]. It is quickly becoming the norm in the developed world that mobile phone devices are outnumbering people. The developing world too has seen a rapid surge in mobile device numbers as mobile networks are often easier and cheaper to install compared to that of landline networks.

As a result of this ever expanding technology, activities that once required a fixed location and connection can now be achieved with higher flexibility, which enables users to act and communicate more freely. The usage patterns obtained from mobile device activity can enable us to model the dynamics of human flow in modern environments [3].

The ability to detect such activity has become increasingly important due to growing interest in the provision of location based services (LBS). LBS researchers have developed techniques for the detection of people in the proximity of an area other than through examining mobile usage statistics. One common approach is to use vision based techniques which utilises camera surveillance systems to identify crowd numbers and behaviour [4], [5], [6]. However, theses types of systems invoke certain social issues with regards to privacy [7], [8].

As stated in Doyle *et al.* [9], the mobile phone usage statistic commonly employed in mobile usage mapping applications is a measure of network bandwidth used. Typically, this is collected at a base station within a mobile operator's network, or by use of special software installed on mobile phones. The metric by which this activity is measured is known as an Erlang. An Erlang is one person-hour of phone use, which could represent one person talking for an hour, two people talking for half an hour each, 30 people each speaking for two minutes, and so on [10]. A more modern interpretation of this metric would be to consider the quantity of digital data transferred, regardless of the form of communication, such as voice, SMS, and data. This method was valuable in the past due to the restricted nature of mobile telecommunications which were fundamentally voice-only networks. Modern networks have an progressively diverse range of usages which do not linearly correspond to intensity of communication. For instance text messaging uses very little bandwidth though is an important form of communication.

As an alternative to collecting data throughput measurements, we have adopted a technique for monitoring the cumulative electromagnetic energy in the frequency band of client-side mobile phone transmissions (i.e. mobile device to base station transmission band). By analysing these RSSI values over time and space through a collaborative network of sensors, we propose that results can be obtained that are of comparable quality to the more invasive network bandwidth metrics (Erlang). Such measurements can be easily achieved using well known circuitry for Received Signal Strength Indication (RSSI) [11], [12]. The information gathered is inherently anonymous due to the absence of information decoding. As a result, it is impossible to deduce individual identities or phone information content from the raw data collected and stored in the proposed system, thus avoiding the potential ethical issues faced by both vision based and network operator polled systems.

In the rest of this paper, we highlight the use of an energy detecting device to monitor mobile spectrum activity for the purpose of mapping mobile device activity. Section II gives an overview of some related work in this field. Section III describes the proposal put forward by this paper. Section IV details the experimental setup adopted to measure the temporal RSSI data, from which useful information is extracted. Section V presents the results of experiments carried out focusing on the collection of RSSI mobile device data under different scenarios. Section VI summarises the conclusions of the work to date and outlines future directions for research.

II. Background

This section presents on overview of some work related to the collection and analysis of human movement data. This can be grouped into real time urban flow mapping, location tracking and spectrum strength collection.

A. Real Time Urban Flow Mapping

The emergence of new mapping applications which present the flux of people in an attempt to demonstrate the dynamics of metropolitan cities highlights the recent growth and interest relating to tracking human flow on urban scales. Over the last few years this research area has seen steady growth with large projects starting in European and Asian cities. The monitoring of mobile phone usage patterns has been the major data source used to extract the human behavioural patterns needed for these applications. Other sources such as passive tolling of Bluetooth devices, as well as techniques including GPS tracking and short range tracking have been utilised in the past but theses do not scale easily in urban environments.

Amsterdam Real Time [13] and Cityware Research Group [14] are examples of such projects. The Amsterdam Real Time project aimed to construct a dynamic map of Amsterdam, Netherlands, based on trace lines produced from the collection of GPS data relating to peoples movements. Each person volunteered in the experiment and was equipped with a GPS receiver. This receiver fed the GPS coordinates of the volunteer to a central system in real time. Maps produced were solely based on this GPS data. In the UK, the Cityware research group supplemented the pedestrian flow data typically gathered as part of a space syntax analysis with data on Bluetooth devices passing through pedestrian survey gates.

To date there are two main methods for the gathering mobile usage information: data collection at the operator level; and through modified mobile phone software. The first area requires the cooperation of mobile operators to provide data on a macro level of urban areas. Graz in Real Time [15], the Mobile Landscapes project [3], Real Time Rome [16] and Bangkok Metropolitan Project [17] are examples of projects which utilised this network operator data.

The Graz in Real Time project is a real time mobile phone monitoring system based on cell phone traffic intensity, traffic migration (hand overs) and traces of registered users as they moved through the city of Graz.

The Mobile Landscapes project collected network usage data in the Milan, Italy. When combined with the geographical mapping of cell areas, a graphical representation of the intensity of urban activities and their evolution through space and time was produced. From this they were able to detect events such as national holidays and major sporting events.

The Real Time Rome was MIT's SENSEable City Laboratory contribution to the 10th International Architecture Exhibition in Venice, Italy. The project was the first example of an urban-wide real time monitoring system that collects and processes data provided by telecommunications networks and transportation systems. It used location data from mobile phone subscribers provided by Telecom Italia, public buses ran by a local transport company Atac and taxis run by the cooperative Samarcanda.

Horanont and Shibasaki [17] presented an implementation of mobile sensing for large-scale urban monitoring in Bangkok Metropolitan, Thailand. They used Erlang data from Advanced Info Service PLC (AIS), a leading mobile operator in Thailand. They showed that large scale monitoring of clusters of Erlang data from mobile base stations were able to provide indirect interpretations of spatial patterns of urban life and its temporal dynamics.

However, there are difficulties with this approach, most notably the legal and privacy issues that prevent operators delivering such information to outside researchers. In addition, even with best efforts, there is no guarantee that data from theses sources is always available, complete or accurate. Network operators continually optimise their network throughout the day, using temporary towers. This adds to the level of uncertainty into these fixed point measurements as network topologies become more dynamic. A more fundamental issue arises regarding spacial accuracy as the spatial resolution of the usage statistics is dependent on both the operators network topology and base station hardware.

As a result approaches have emerged which aimed to address these issues by placing embedded software applications on the mobile devices to log data. Estonia group project [18] and MITs Reality Mining project [19] are examples of projects which utilise this approach.

Ahas and Mark [18] tracked the mobile phones of 300 users for a social positioning application. They combined spatio-temporal data from phones with demographic and attitudinal data from surveys, creating a map of social spaces in Estonia.

MITs Reality Mining project illustrated that it was possible to extract common behavioural patterns from the activities of 94 subjects. The subjects were issued with mobile phones pre-installed with several pieces of software that record and sent research data on call logs, Bluetooth devices in proximity, cell tower IDs, application usage, and phone status. This yields valuable, person specific results but the solution may not be easy to scale considering the large numbers needed to represent urban and suburban populations.

B. Mobile Phone Location Tracking

Most indoor environment based localisation research to date has focused on the accurate localisation of objects and people using short-range signals, such as WiFi [20], [21], [22], Bluetooth [23], ultra sound [24], and infra-red [25]. Outdoor localisation is almost exclusively performed using the Global Positioning System (GPS).

Otsason *et al.* [26] showed that an indoor localisation system based on wide-area GSM fingerprints can achieve high accuracy, and is in fact comparable to an 802.11-based implementation. To date there are two major ways for mobile phone locations to be tracked in mobile networks, namely network-centric and device-centric localisation. In network-centric systems, base stations make the measurements of distance to a mobile phone and send the results to a centralised location at which the location of the mobile device is calculated. In device-centric systems, the handset performs the calculation itself on the basis of environmental information gathered from the network. Hybrid solutions are also possible, which try to combine the advantages of both.

The American National Standards Institute (ANSI) and the European Telecommunications Standards Institute (ETSI) stated that mobile positioning systems can be classified under the following technologies: cell identification, angle of arrival, time of arrival, enhanced observed time difference, and assisted GPS [3].

- *Cell identification;* The available coordinates of the serving base station are associated with the mobile device. The accuracy of the locational information depends upon the physical topology of the network.
- *Angle of arrival (AoA);* The AoA method uses data from base stations that have been augmented using arrays of smart antennas. This allows the base station to determine the angle of incoming radio signals, making it possible to then determine the location of a handset by triangulating known signal angles from at least two base stations.
- *Time of arrival (ToA);* Position here is determined by triangulating the time needed for a packet to be send from a phone to three finely synchronised base stations and back.
- *Enhanced observed time difference (E-OTD);* This requires handsets to be equipped with software that locally computes location. Three or more synchronised base stations transmit signal times to the mobile device, the embedded software of which calculates time differences and therefore distance from each base station making triangulation possible.
- *Assisted global positioning system (A-GPS);* Here devices use both GPS and a terrestrial cellular network to obtain geographic positioning.

C. Spectrum Signal Strength Collection

To collect the cumulative electromagnetic energy in the frequency range of client-side mobile phone transmissions, one must be able to measure and quantify the energy in the specific energy band occupied by client-side mobile phone transmissions. This is effectively measuring the signal strength in a specific frequency band of energy [11], a common technique in wireless communications. To do this reliably an energy detecting device is used which returns a received signal strength indication (RSSI) parameter. Energy detecting devices can easily be purchased or built. Due to such readiness in availability, RSSI has been considered in the past as a sensing parameter. A number of applications have provided insight into its usefulness, both Wu *et al.* [27] and Stoyanova *et al.* [28], in particular, describe the key issues which affect RSSI accuracy. They are summarised as:

- The orientation of the antenna;
- Transceiver variation;
- Multipath fading and changes in environment.

Multipath fading and environment changes contribute the main variance in RSSI data. This relates to part of the electromagnetic energy radiated by the antenna of a transmitter reaching a receiver by propagating through different paths. Along these paths, interactions known as propagation mechanisms may occur between the electromagnetic field and various objects. To model theses mechanisms, propagation prediction models have been devised to provide an accurate estimate of the mean received power or path loss (PL) for a specified frequency band based on geographical information about the environment. Empirical, semi-deterministic, and deterministic models are the main classes which describe mobile channel characteristics [29]. As these propagation models describe how a signal may act in a given environment, they must be used when trying to gain insight into positions of signal sources.

In recent years cognitive radio systems [30], [31], [32] have become increasingly viable and signal strength measurement is a key element in the detection of primary user spectral occupancy. To improve performance, they have explored a number of techniques that can be used to address these issues, such as collaborative sensing between multiple RSSI detectors [33], [34]. By cross-correlation and signal processing, non-random signals can be detected and analysed. Similar approaches can be applied with existing transmissions to detect usage and extract statistical patterns.

III. Proposal

Our proposal is based on the measurement of localised cumulative strength of mobile device emissions through the use of an RSSI sensor. We propose that this data can provide a suitable alternative to operator obtained data. Results will demonstrate the proposed method can capture mobile phone activity and display the spacio-temporal patterns contained within.

As an alternative sensing parameter, cumulative received signal strength (RSSI) offers several advantages over network usage data;

- RSSI data can be collected without the cooperation of mobile operators or mobile device user.
- RSSI as a metric is independent of modulation type, so RSSI can be used for GSM protocols and 3G protocols.
- Geo-spatial RSSI data can provide fine resolution making it possible to localise events very accurately and quickly.
- RSSI collection hardware can easily be modified to observe different metrics, making a network deployment very flexible.

However, individual sensor measurements of wideband signal strength measurements have limitations in terms of localised accuracy. This is due to limiting channel characteristics and the inability to distinguish between a single near device transmitting with high power and several users far away transmitting with low power. The question then is how to reliably collect this information taking into account such factors.

By adopting techniques commonly utilised in cognitive radio systems, we propose that these accuracy issues may be mitigated. First, by spatially and temporally weighting each RSSI data point form a sensor with corresponding points from other radios in the geographical area nearby, the RSSI accuracy can be improved [33] [34]. Second, modelling the environment with accurate models will help quantify the data and give insight into its behaviour. Third, calibration with respect to base station coverage will reduce effects caused by mobile device transmission power variation. Finally, the spatial sampling topology of the sensor network will be a dominant factor in determining performance, particularly when variable sensor heights are also considered. Thus methods for insuring topology uniformity must be taken into account.

To distinguish between the RSSI signal generated by one user near the sensor and several users further away we will deploy a dense network topology. This will insure that spectral energy readings from each sensor can be localised to some degree. To localise such activity there are several possible solutions. One is to localise activity based on a sensor identification technique, similar to the cell identification used to identify a mobile device position in a cellular network. Here the sensor node with the associated highest RSSI value is deemed to be the coordinate of the activity. This will however offer reduced spatial resolution. Thus a more advanced technique, which combines multi-sensor information, would be a more suitable approach.

IV. Experimental Work

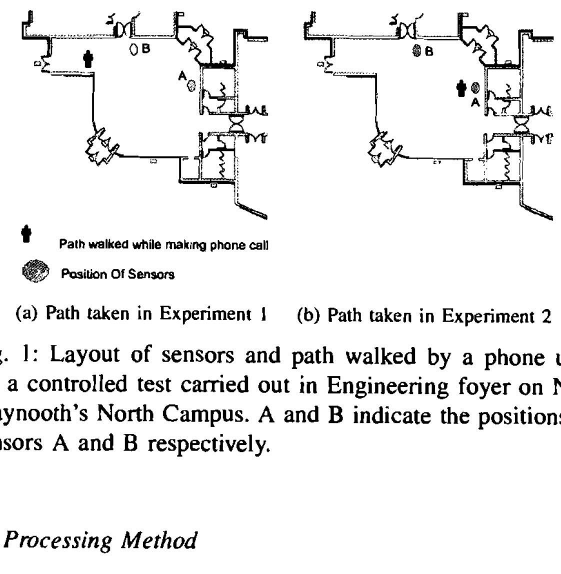
A. Experimental Setup

Our experiments were based on the measurement of localised cumulative strength of mobile device emissions through the use of a custom-made RSSI sensor. The main component used to measure the RSSI intensity was a true power detector from Analog Devices (chip part number AD8362) paired with a single omni-directional GSM 900 antenna. The AD8362 device returns a voltage which linearly corresponds to the RF spectrum power passed through it. It operates with a 65dB dynamic range, ranging from -55dB to 10dB. To obtain a measure of the performance, experiments were carried out within a building on NUI Maynooths North Campus. The measured performance of two such sensors were compared to that of a spectrum analyser, the results of which can be found in Section V.

Doyle *et al.* [9] described the capabilities of such a sensor with respect to picking up different types of phone activity. This paper highlighted the capability of such sensors for picking up even shorter bursts of mobile transmission energy with both text message and phone call activity clearly identified. A technique for the extraction of areas of high temporal dense activity was also demonstrated. From this information, areas around each hour mark of high temporal density were highlighted, these times coincided with the starting and finishing times of lectures, thus demonstrating that RSSI can provide the information needed to monitor human behaviour.

To further validate the capabilities of the sensing devices and feature extraction methodology, we designed two experiments which tested different scenarios of mobile phone activity. The focus was to test our method for geo-spatial temporal weighted signal processing. Both experiments took place in the foyer of the Engineering building at NUI Maynooth under controlled conditions (no other phone activity). The result can be seen in Section V.

- **Experiment 1:** Obtain RSSI measurements from a phone call while a person is walking in a uniform direction. The path taken is depicted in Fig. 1a.
- **Experiment 2:** Measure readings from a phone call while a person is walking in a non-uniform direction. The path taken is depicted in Fig. 1b.



(a) Path taken in Experiment 1 (b) Path taken in Experiment 2

Fig. 1: Layout of sensors and path walked by a phone user for a controlled test carried out in Engineering foyer on NUI Maynooth's North Campus. A and B indicate the positions of sensors A and B respectively.

B. Processing Method

Various signal processing algorithms can be applied to assist with extracting interesting patterns from measured mobile phone signal strengths. Our approach has focused on a geospactial temporal based scheme that identifies time periods with interesting behaviour. One early implementation is explained in this Section. Its layout is depicted in Fig. 2.

The spectral energy, which was sampled at a rate of 2kHz, and is denoted as $s(k)$. The signal processing method applied to these samples consists of four stages.

- **Stage 1:** Detect the presence of a mobile transmission as governed by a cut-off threshold τ

$$s_\tau(k) = \begin{cases} 0 & \text{if } s(k) < \tau \\ s(k) & \text{if } s(k) \geq \tau \end{cases} \tag{1}$$

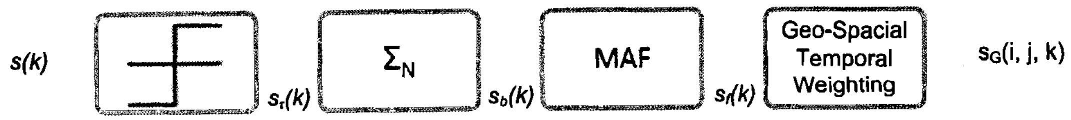


Fig. 2: Signal processing performed on raw RSSI data. Feeding output back into the geo-spactial temporal weighting stage gives an n^{th} order weighting.

where τ in this instance is chosen to be -55dBm, the minimum detectable level of the energy detecting chipset.

- **Stage 2:** Downsample the data by a factor of T, this is done by replacing every block of T samples by its average

$$s_b(i) = \frac{1}{T} \sum_{k=(i-1)T+1}^{iT} s_\tau(k) \tag{2}$$

where $s_b(i)$ is the downsampled data set and T is the downsampling factor. Decimation should be application specific. While it can trim down the noise within the data, excessive decimation may reduce the signal of short temporal events, such as text messages.

- **Stage 3:** Smooth the data using a moving average filter (MAF) of width $(2W + 1)$ samples

$$s_f(i) = \frac{1}{2W+1} \sum_{p=(i-W)}^{i+W} s_b(p) \tag{3}$$

where $s_f(i)$ is the resulting filtered data set.

- **Stage 4:** Given a vector of readings from a set of n sensors

$$\mathbf{s}(k) = [s_1(k), s_2(k), s_3(k), \ldots, s_n(k)] \tag{4}$$

apply a geo-spatial temporal weighting using a truncated Gaussian Kernel. Here, $s_i(k)$ the sensor reading from the i'th sensor, has an associated coordinate in space (x_i, y_i) relating to the position of the sensor. To achieve this weighting, points are calculated in space-time by a collaborative weighting of readings taken from each sensor node. A point in space-time $s_G(x, y, k)$ can be calculated using,

$$s_G(x, y, k) = \sum_{p=k-j}^{k+j} \sum_{i=1}^{n} g_{ip}(x, y, k) s_i(p) \tag{5}$$

where $g_{ip}(x, y, k)$ is the geo-spatial temporal weight corresponding to reading $s_i(p)$ and $2j + 1$ is the width of the truncating window in time. The weight $g_{ip}(x, y, k)$ is given by

$$g_{ip}(x, y, k) = g_\beta(x, x_i) g_\beta(y, y_i) g_\beta(k, p) \tag{6}$$

where

$$g_\beta(u, v) = e^{-\left(\frac{u-v}{\sigma_u \beta}\right)^2}. \tag{7}$$

Here, u and v are placeholders for the corresponding variables in Eq. 6. σ_u denotes the initial spreading factor assigned to each dimension and β is a scaling factor controlling the spread given to those points whose weight is over the lower limiting threshold γ such that,

$$\beta = \begin{cases} 1 & \text{if } s_i(k) < \gamma \\ c & \text{if } s_i(k) \geq \gamma \end{cases} \tag{8}$$

where $c > 1$. The effect of this stage is to weight each RSSI data point from a sensor with corresponding spatial and temporal points from other sources such that readings that are both spatially and temporally close are amplified.

V. Results

The results shown here reflect measurements of wide band mobile phone RSSI taken on NUI Maynooth North Campus. Fig. 4 illustrates the sensitivity comparison between a spectrum analyser and RSSI sensors, whose architecture is described in Section IV-A. It can be seen that the readings from RSSI sensors, though less precise, resemble that from a spectrum analyser.

Fig. 3 presents the measurements collected in an experiment prior to geo-spatial temporal weighting. The experiments are carried out to verify the ability of signal processing algorithm to highlight the movement of mobile devices in an indoor environment. Fig. 5 and Fig. 6 show how the geo-spatially temporally weighted points in space may be visualised in the form of contour maps that highlight device activity picked up.

The temporal shift of energy can clearly be observed as the positions of the phone calls, in voice communication mode, vary in space. Currently, a preliminary method is employed to interpolate the data over space. This consisted of adopting the sensor nodes positions as the centre of energy annealing the signal as we moved further out. Note weights represented in each contour plot are relative measures compared to that of surrounding areas. As a result the measure of dominance should be considered relative and not as an absolute value.

Future work will involve more advanced methods which may take into account pre-defined information gathered from geographical information systems (GIS) and channel models relating to the mobile spectrum band of interest. Nevertheless,

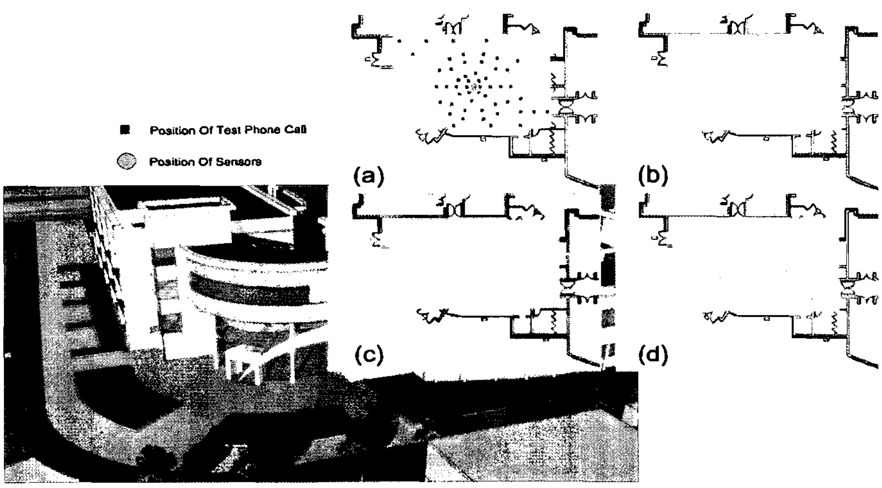
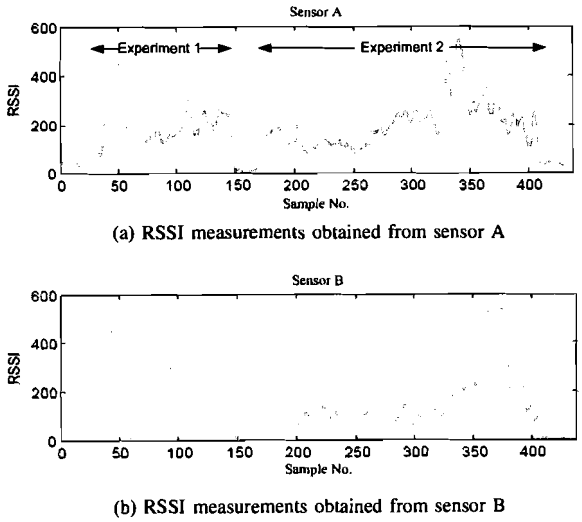
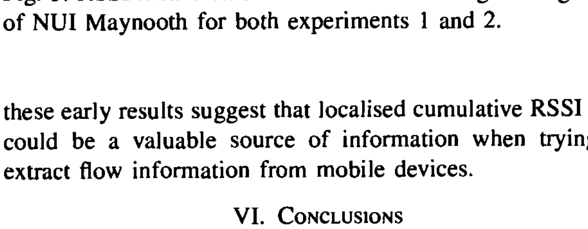


Fig. 4: RSSI measurements obtained in the foyer of NUI Maynooth's Electronic Engineering building showing the relationship between the sensor nodes used and a spectrum analyser: (a) locations of calls made in the foyer, the positions of the sensing nodes and spectrum analyser; (b) readings taken from a spectrum analyser; (c) readings taken from sensor A; (d) readings taken from sensor B



(a) RSSI measurements obtained from sensor A



(b) RSSI measurements obtained from sensor B

Fig. 3: RSSI measurements obtained in the Engineering foyer of NUI Maynooth for both experiments 1 and 2.

these early results suggest that localised cumulative RSSI data could be a valuable source of information when trying to extract flow information from mobile devices.

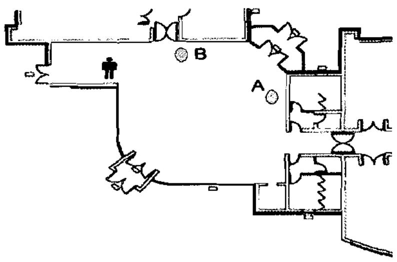
VI. Conclusions

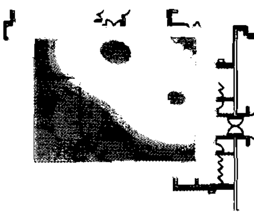
This paper summarised the work being carried out in the area of mapping mobile phone activity on urban and localised scales. At the same time, an overview is presented on popular localised tracking techniques and issues which relate to the reliable measurement of mobile spectrum RSSI. Experiments demonstrate that the detection of mobile spectrum RSSI can provide useful information when monitoring mobile device activity in a localised context. This information is gathered without the cooperation of mobile network operators or users and retains usage anonymity due to the lack of information decoding. We presented a preliminary technique for the detection and visualisation of mobile activity flow within indoor environments.

This proposed approach could also be used to complement traditional techniques for mapping mobile device activity. For instance, one could use the network operator data, if available, to model the dynamics of a city or town while localised RSSI data, within such an urban environment, is used to observe the dynamics of specific buildings or localised areas. Nonetheless, our research is still in its preliminary stages, so additional validation is needed.

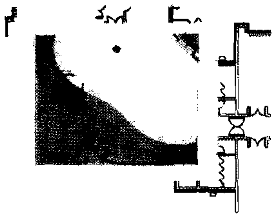
For this purpose, a mobile sensor network aimed at the collection of RSSI data is under construction. It will first be distributed throughout the North Campus of NUI Maynooth with a view to expanding it into the nearby South Campus and town of Maynooth in longer term. This project will offer an opportunity to understand some of the dynamics relating to university student life. Moreover, focusing on temporal and spatial patterns of mobile phone activity may shed light on how we interact with our local environment.

We hope to address such questions as how buildings really used on campus, how to determine where people can be found as opposed to where they pass through and how to identify interesting localised events as they occur in time and space. The answers to these questions would pave the way for a number of interesting applications. A real time map of human

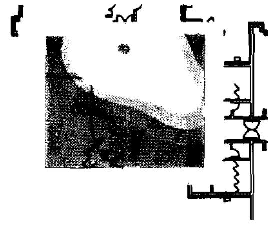




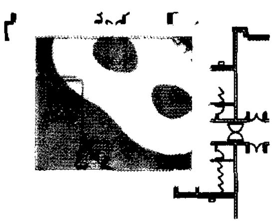
(b) Sampled at 12.5s



(c) Sampled at 18.75s



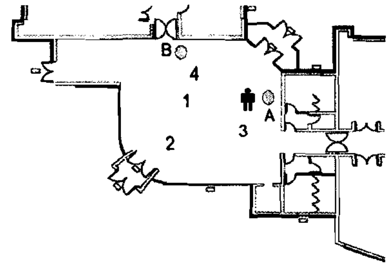
(d) Sampled at 25s

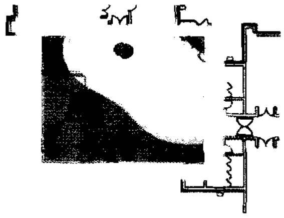


(e) Sampled at 31.25s

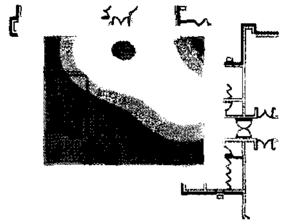
Fig. 5: Mapping of RSSI information obtained after the geo-spatial temporal weighting process for time slot of experiment 1 in Fig. 3 at different sampling times.

flow could be produced showing the real time movements of student population, both indoor and outdoor. The map could provide insights to university planning authorities to decide on the location of student services or emergency services in the event where rapid response is required.

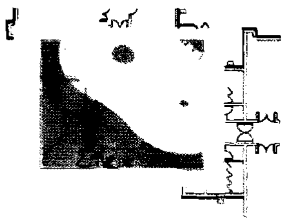




(b) Sampled at 50s



(c) Sampled at 62.5s



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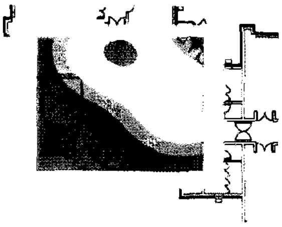
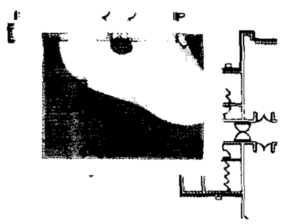


(e) Sampled at 87.5s



(f) Sampled at 100s

Fig. 6: Mapping of RSSI information obtained after the geo-spatial temporal weighting process for time slot of experiment 2 in Fig. 3 at different sampling times. The path numbers indicate the walking sequence of the phone user.

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