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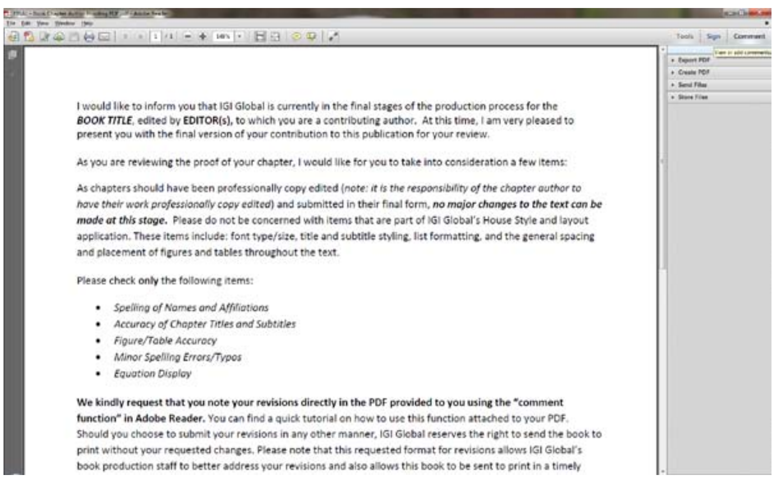

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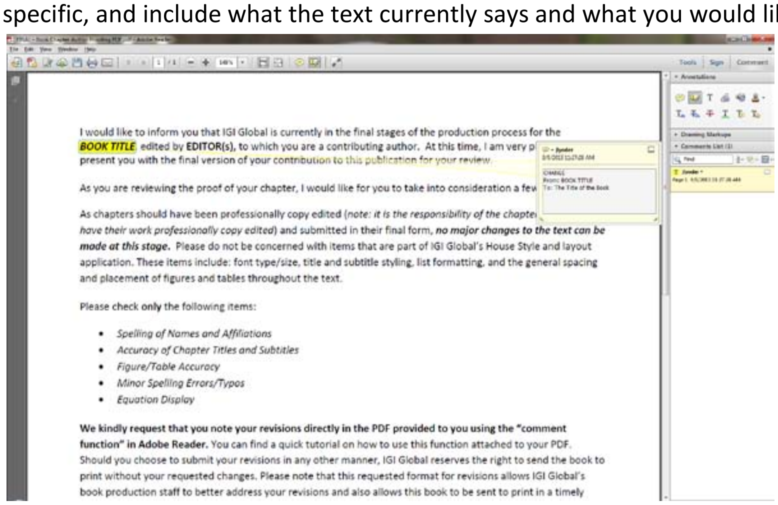

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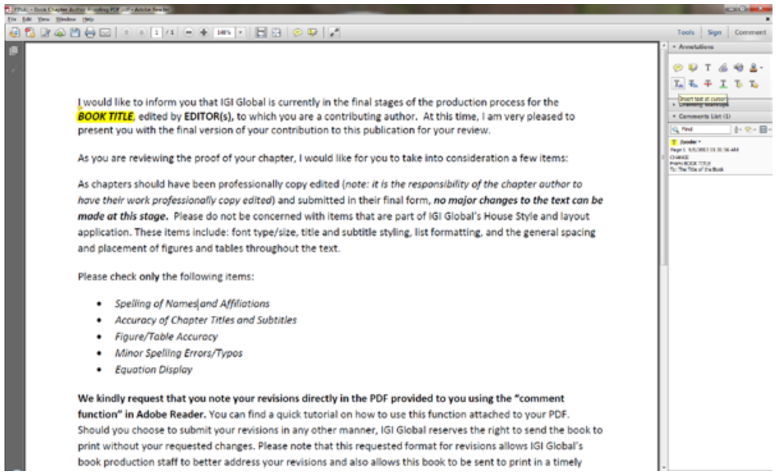

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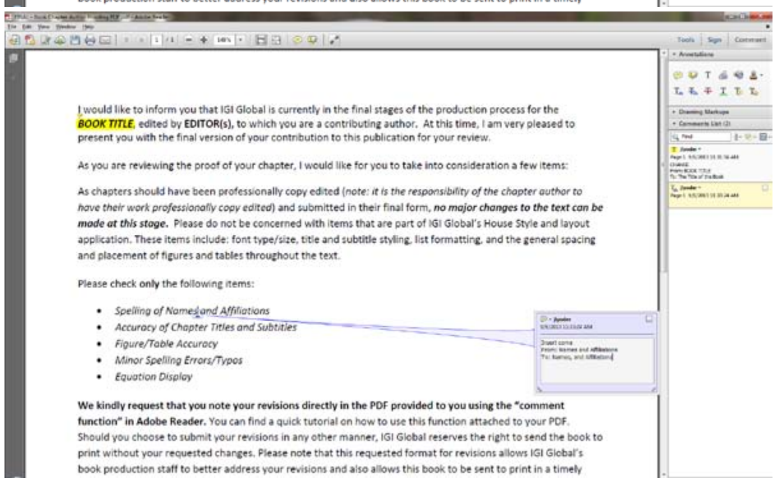

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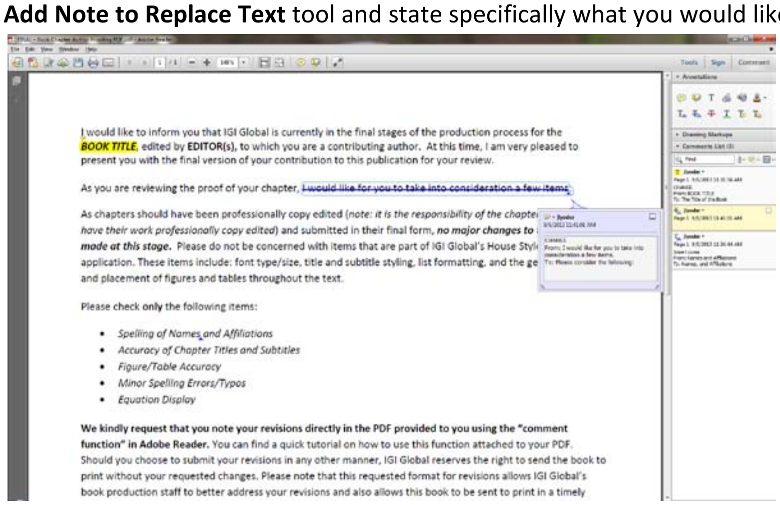

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Detection of Social Interaction Using Mobile Phones via Device Free Passive Localisation

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ABSTRACT

Mobile devices which make use of 802.11 Wi-Fi are ubiquitous in modern society. At the same time, there is an unmet need in research and monitoring applications, and particularly in those relating to service and health-care scenarios, to accurately detect the occurrence and hence frequency and duration of human interaction between subjects. Various sensor modalities exist that are able to perform localization of human subjects with useful degrees of accuracy, but in all cases they are either expensive, inflexible, or prone to influencing subject behaviour via the Hawthorne or observer effect. Given the ubiquity of mobile devices, it is the contention of this paper that a system which localizes human presence based on the human body's obstructive effects on RF transmissions through interpretation of perturbation of the Received Signal Strength values generated during transmission, may offer a system that is both inexpensive and flexible, while avoiding the need for direct subject participation, and thus reducing the impact of the Hawthorne effect.

Keywords: *Behaviour Detection, Device-free Passive Localisation, Indoor Localisation, Mobile, Movement Detection*

1. INTRODUCTION

The ability to track human motion or detect when a person is present in an area is valuable in a variety of circumstances. Besides surveillance and security applications, for which the utility is obvious, there are multiple service and care scenarios in which these functions are also of use. The IR sensor on an automatic door would be a simple example of the former, while a tracking bracelet worn by a dementia patient is the same to the latter. Research on human behaviour, focussed on capturing the normal activity of human subjects, also benefits from these technologies, in many contexts and via diverse monitoring strategies. In each of these three cases the requirement is to obtain information on human activity at the necessary level of accuracy, while minimising intrusion and cost. Costing must cover both equipment purchase and installation time/fees, and is minimised for obvious reasons. Intrusiveness is more subtle, as it can have an

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indirect impact on accuracy or ease of use. The Hawthorne effect (Landsberger, 1958) is that in which individuals modify their behaviour based upon the readily apparent fact that they are being observed in a given situation. The presence of a visible observer or monitoring device causes people to behave other than they usually would, thereby decreasing the accuracy of any recorded research data. Likewise, a system which requires that participants wear or interact with unwieldy equipment is less easy to use.

Therefore, the ideal system for monitoring human activity is one which is cheap, unobtrusive, and sufficiently accurate. Device-free passive localisation (DfPL) is one class of such human activity monitoring systems. Passive localization differs from active localisation insofar as that in order to perform active localisation, participants or users must carry some form of monitoring device upon their person. With reference to the previous examples, an automatic door is a passive sensor, whereas a locator bracelet detector is an active sensor. Cost for such devices may be nominal, but any approach that requires active participation will be intrusive to some extent. DfPL avoids these concerns by functioning without any such requirement – it is "device free" in that no equipment must be carried by participants. In DfPL, the sensing component takes advantage of the absorption and scattering effects of human bodies on RF radiation, particularly around the range of 2.4 GHz, which is common to all Wi-Fi standards, and which also is strongly absorbed by water, of which human bodies are largely composed. Environmental blockage, such as furniture and human bodies in the vicinity of the receiver or transmitter cause deep fades that might limit the range and the performance of short-range wireless systems (Deak et al., 2013).

Although this is an issue for maintenance of a connection which becomes obstructed by a human body, it does mean that a wireless link between a device and an AP has some degree of ability to sense changes in the level of obstruction between the two. Previous studies have shown that the signal level exceeds the average level when the person is close to the link but not blocking it (Kara and Bertoni, 2006; Deak et al., 2014), which means that as a person enters, occludes, and leaves the main body of a signal path, their passage creates a series of perturbations in the Received Signal Strength Indication (RSSI) recorded on receipt of a data packet that can be used to infer motion through that path.

The particular implementation of DFPL discussed in this paper uses a standard Wi-Fi access point (AP) linked to a number of ordinary smartphones dispersed around a room in static positions as its sensing infrastructure, and requires no further equipment. In this way it satisfies the requirement for cost, in that smartphones are ubiquitous and therefore represent a sunken cost, as too with Wi-Fi APs. There is also minimal overhead for installation, as all that is required is for the mobile phones to be placed at certain positions in a room within range of an AP. Therefore, this system is both cheap and unobtrusive. We demonstrate our system working in an area of research in human behaviour, that of human interaction. This could be of use in social science, or in study into care for the elderly or those with physical or mental impairment, in which the frequency of human interaction is believed to form an important role in the quality of care. A simplistic description of human interaction is that it requires two or more people to be present, and to be speaking to each other. An extension of the usefulness of mobile devices is also possible, as in addition to Wi-Fi connectivity, mobile phones also have microphones. Therefore, this paper outlines a system which combines the technique of RSSI DFPL to detect when several individuals are in close proximity, with mobile phone audio sensing. It measures human interaction, via a low cost sensing network comprised of generic commercial devices combined with intelligent machine learning techniques.

2. LOCALISATION TECHNIQUES

The ubiquity of mobile devices in modern society offers opportunities previously not available in all research and monitoring applications. One possible implementation uses RSSI as the sensing medium. RSSI is a MAC layer indication of the strength of a received packet. It is useful mainly because it is easily accessible – any off-the-shelf device which makes use of 802.11 standards will have an RSSI calculator integrated into its circuitry. This makes mobile phones ideal for any implementation of RSSI localization which seeks to minimise cost, although more specialised hardware can provide reduce systematic inaccuracy. Inaccuracy is introduced into any such localization system by virtue of the properties of RF propagation - in most indoor spaces there will be furniture, walls and miscellaneous obstacles of varying sizes, shapes, and material construction. Heterogeneous environments of this type firstly introduce multiple factors which influence RF propagation. For example, multipath propagation is the case in which, due to the varying reflective properties of different surfaces, multiple routes exist between sending and receiving devices. Packets leaving one may reach the other directly, giving a short time of flight (ToF), high RSSI, and particular angle of incidence, whereas a packet reflected off several surfaces before reaching its destination may have a much longer relative ToF, lower RSSI, and completely different incident angle. Each of these values can be used in localization, and therefore multipath propagation is a serious problem for any localisation system based on RF transmission. Likewise, RF transmission is subject to interference from the many other RF sources present in the modern setting. This is not limited to overlapping 802.11 devices active on similar frequencies – fluorescent lighting, cordless console controllers or telephones and even microwave ovens (Murakami et al., 2003) can interfere with a sensing network of 802.11 devices. Another challenge to any system which is desired to be easily deployable is that indoor environments are heterogeneous. Therefore, it is not possible to design a system which is hard-coded to compensate from sources of error in all contexts. More expensive hardware can ameliorate these and other issues, but it is however possible to design adaptability into such a system using off-the-shelf hardware – the difficulty of such design is the main obstacle to effective use of RSSI in a low cost context.

2.1. Active RSSI Localisation

RSSI can be used to perform localization in both an active and a passive mode. An advantage of the active mode is that it gives a direct reading of the signal strength between a carried mobile node and multiple access points. Given that AP locations are generally known and that signal overlap is desirable (multiple APs covering the same area on different channels) this allows for various forms of RSSI processing to provide relative or absolute localisation of a connected mobile node. Luo et al. (2011) describe and compare some implementations of this, all of which base their calculations on the fact that signal strength is inversely proportional to the distance between AP and node. With three or more APs in range, a node can be localised in two dimensions through several forms of algorithmic triangulation. For example, a mobile node first receives the distance between each AP in the network. These distances form radii, which are grouped into those greater than or lesser than the inferred distance between each AP and the mobile node. If the distance to the first AP (inferred via RSSI) is greater than the distance between that AP and a second, then the mobile node lies outside of the circle centred on the first AP, whose circumference intersects the second. If the distance between the first and second is less than that between the AP and the mobile node, it lies within the corresponding circle. Overlaying these circles in the manner of a Venn diagram, the mobile node narrows down its location, with its estimation accuracy growing with the addition of each AP pair. If the location of each AP is known, then the localisation is absolute – if not, then the location is relative. Luo et al. achieved average accuracy of between 1.5m and 3.1m with this system – given that this was tested in a cluttered live environment, this represents a relatively useful result for some localization scenarios.

Conceptually simpler algorithmic implementations are also viable. Jiing-Yi et al. (2012) use an anchor node network deployed in a regular arrangement in which the target mobile node uses a calibrated power decay curve to determine the nearest three anchors – it then builds the location of each anchor into a triangle with one anchor at each vertex. The position of the target is estimated with good accuracy to be at the centroid of the triangle thus formed. This implementation deals with the problems inherent to RF-based localization schemes (multipath etc.) through its clever calibration method. The power decay curve is used to establish the minimum power required to establish a connection with a node at a given range. When sensing, the transmission power is slowly increased until it is only just sufficient to reach the target. This method reduces the impact of multipath propagation greatly, as packets which travel by a longer route do not have the power necessary to be sensed by the receiver. It does however suggest that this system may be more susceptible to interference. Nonetheless, in a test environment, (Jiing-Yi et al., 2012) achieved an average error of around 0.4m, showing that RSSI localization systems can be implemented in realistic environments with a high degree of accuracy.

Some experimental implementations were less successful, and in many cases this seems to be because issues such as multipath etc. have not been accounted for. Dong and Dargie (2012) found RSSI-based localization to be "unreliable as the only input to determine the location of a mobile node in an indoor environment", which, even after various smoothing methods, recorded very high instability in their data, especially at ranges closest to the receiver. This may have been in part due to their test environment – a long narrow corridor bordered by a concrete wall, and a long window. It seems reasonable to expect that this environment would produce severe multipath effects – this illustrates the fact that any implementation of RF-based localization must take such characteristics of the medium into account. Nonetheless it can be seen that properly implemented RSSI-based active localization can potentially offer localization with accuracy around the range of 1m, which is sufficient for the purpose of detecting when two humans are within proximity suitable for interaction. However, it is the intent of this project to provide this function in the passive mode, and so the passive mode in general will now be discussed.

2.2. Passive Localisation

Passive localisation is necessarily less accurate than active localisation for a given relative sensor resolution, given that more must be determined by inference rather than direct measurement – there is not necessarily direct proportionality between any single sensor reading and the range of the sensor to the target. Even when a direct proportionality does exist, the confidence boundaries on each range estimate will be larger, and more subject to interference, given that the target is neither the source nor the receiver of any signal. Despite this, it is still possible to estimate the position of a target in the imaging area of a sensor network, via inference from either direct perturbations of the substance of the system itself, or indirect perturbations in the medium of the environment, sensed by the system. A pressure plate upon which a target rests might give a reading of the former type, whereas a camera which receives light reflected from a target might give a reading of the latter type.

2.2.1. Passive Non-RSSI Localisation

Multiple localization approaches which do not use RSSI have been available for many years, but all have inherent drawbacks outside of spaces specialised to some extent towards monitoring.

At the same time, they do not suffer from the multiple drawbacks of dealing with RF propagation. Therefore it is worthwhile to consider some implementations to compare their suitability to the stated scenario (low cost, ad hoc, and easily deployable) with RSSI-based approaches. For example, it was found to be possible to perform motion tracking of several individuals simultaneously between multiple surveillance cameras (Cai and Aggarwal, 1996). Later the algorithmic back-end of this sensor modality was expanded to perform accurate tracking without the heavy processing load required by pattern extraction/feature matching (Khan et al., 2001; Beleznai et al., 2005), but, these improvements aside, the infrastructure requirements of camera installation and the privacy concerns raised by constant monitoring make this approach unsuitable in many contexts. Alternatively, pressure sensitive floor overlay was found to track location and hence motion with a good degree of accuracy, for example using InfoFloor tiling (Murakita et al., 2004) or TileTrack tiling (Valtonen et al., 2009), and was cheap on a per-unit basis. However, it becomes expensive when covering a large area, and is not appropriate for some floor surfaces. Also the sensors were large, and could not differentiate between two persons standing closely together. Both InfoFloor and TileTrack are now defunct, suggesting that it was not a commercially viable approach. Alternative overlay approaches such as Z-Tiles (Richardson et al., 2004) reduce the sensor size and thus improve resolution, but at increased cost per area covered, especially when including installation costs, and are still unsuitable for many surfaces. An underlay such as SensFloor (Lauterbach et al., 2012) is both relatively cheap at scale, and of adequate resolution for tracking of multiple persons, but however it requires that it be installed under soft floor covering, which in the case of later installation means that the current covering must be lifted and subsequently replaced.

Any implementation of a pressure-based localization system must consider the issues with scaling and installation of proprioceptive sensors, with the result that it is generally not suitable if flexibility or low cost are required. More esoteric systems have also been developed. Short-range radar systems are available on the market, and allow the use of ultra-wideband radio to detect motion through walls and other non-metallic obstacles. They are effective in doing so (Frazier 1996) and have been refined to become more accurate over the years (Xin et al., 2014), but their high cost and specific utility limit their use to military, law enforcement and disaster triage applications in which the cost can be justified. Sonar is also a viable option for human motion tracking in specific contexts, as it is effective at moderate range underwater (DeMarco et al., 2013), but in air the inaccuracy at range introduced by the instability/variability of the physical medium exceeds current signal processing capabilities (Schillebeeckx, 2012), and thus restricts the scanning area below that which is useful.In each case either the cost of the system (or system installation), inherent systematic inflexibility, or the privacy concerns raised, make these methods unsuitable in non-specialised spaces or environments. Therefore, in contexts where a low cost system is required, and in which minimal setup requirements are valuable, RSSI-based DFPL may offer a cheaper and more flexible alternative.

2.1.2. Passive RSSI Detection

As stated, the main advantage for this project of a passive localization system over an active one is to remove the requirement of participation from observed subjects, thus reducing susceptibility to the Hawthorne effect. However, the passive systems discussed above either do not satisfy this requirement (e.g. cameras), are expensive (e.g. radar, SensFloor), are inflexible (e.g. most pressure sensors, sonar) or lack the required resolution (e.g. tile overlays). Given that it has been shown that active RSSI localization can satisfy all but the first requirement, it is desirable that a passive RSSI implementation provide something approaching the utility, cost, and most importantly accuracy, provided by RSSI in the active mode, in addition to the benefit of the passive mode itself. Kara and Bertoni (2006) showed that human presence can have a large impact on RSSI values. To begin, detection of the presence of a human is a simpler task than localization of that presence. Passive RSSI techniques have been shown sufficient to this task many times – for example Mrazovac et al. (2013) used calculations based on measurement of entropy inferred from RSSI values to detect human presence with accuracy exceeding that of passive infra-red (PIR) sensors. In two different scenarios, using indoor spaces with a normal mixture of heterogeneous obstacles, their RSSI based detection outperformed PIR in each case, with PIR having a detection rate of around 75% in each, whereas their RSSI detection achieved 100% and 91% respectively. A particular advantage of RSSI in their implementation was that it could detect stationary human presence, in addition to motion, which PIR is specialized towards. They further found, with regard to perturbation in RSSI levels, that "The degree of variations is correlated with the level of human motion" (p. 300), suggesting that in addition to bare detection, some details regarding motion can also be inferred. Their findings are supported by the work of Wang et al. (2014), who note that when in the vicinity of a Wi-Fi transceiver "the human body has a huge impact to the RSSI value". They find that a static human body occluding the path of transmission between two nodes causes a decrease in the RSSI level which is stable. Additionally, they find that entering or exiting this path is accompanied by a large fluctuation in this level, with both a positive and negative component, a fact which is used by some studies not discussed in this paper to aid in the classification of a motion event.

2.1.3. Passive RSSI Localization via Mapping/Fingerprinting

Determining a target's location with precision is more difficult however. A great many differing approaches have been attempted, with varying levels of success, but the specific concept of Device Free Passive Localisation was introduced by Youssef et al. (2007). After first testing whether RSSI data could be used to infer presence, and finding that they could do so (twice, using two different probabilistic calculations based on perturbations of the RSSI ground state of their test environment) with 100% accuracy, their next step was to create a radio map of the environment. This was stored as a histogram of the RSSI values at the receiving nodes when a person is standing at each point in the map, with a separate version of the map created for each node/AP pair. Now, when a person was standing at any given point in their test area, they were able to use Bayesian inference to determine the probability that they were at any of the points on the map, and localized the person at whichever of these returned the highest probability. This method enabled them to localize with an accuracy of around 0.2m, and although the paper does not give any measurements of the test area, it comprised five rooms, a hallway, two transmitters and two receivers, for which reason it seems safe to conclude that their results were impressively precise. This is not to say that their experiment presents a suitable implementation of this system for everyday use however. Several issues are raised in the paper without being resolved such as:

1. The radio map must be manually generated, which increases the setup time proportional to the number of points recorded in the map.
2. The map was created with a person standing each of only four points, but it would be desirable for such a system to locate presence at any point within the scanned area.
3. They did not investigate the issue of multi-occupancy of the space, which would generate an entirely different RSSI pattern to single occupancy, and would need to be handled by any practical implementation of such a system, especially one aimed at detecting proximity of multiple individuals.

4. They raise the issue that changes in environmental conditions such as heat, humidity and RF interference would decrease the accuracy of their base RSSI map, which once again would need to be accounted for should this system see real use.

The solution they suggest for each of these four problems is to create a system wherein the RSSI map may be automatically generated, and recreated as necessary in response to changing conditions. Youssef returns to this question in (Aly and Youssef, 2013), in which they create a system which takes as input a 3D model of the test environment, and then using known details of the properties of the material construction of the environment and the specifications of the sensing hardware automatically creates a map of the area. In this map, ray tracing simulates RF propagation, and generates a prediction of the received RSSI values when a human stands at one of 44 points within a $66m^2$ model apartment. In their most successful configuration of this system, they were able to determine the location of an individual with average error of 1.44m. However, this is only a partial solution to the problem. Although the accuracy is still useful, though lower than that achieved in the simpler first version of the experiment, this method only resolves two of the four stated problems, and even then only partially. The fact that the map is automatically generated saves on the laborious process of manual mapping, but this is replaced with the need to obtain an accurate 3D model of the environment, in which the materials of each obstacle and feature are known. Secondly, the number of mapped points is increased, but it is tuned to discrete points, rather than a continuous function. Also, the model still only accounts for single occupancy, and it seems fair to imagine that generation of additional persons would represent a geometrical increase in required simulation time, and finally because it is generated in simulation, it cannot account for changing environmental factors.

2.1.4. Passive RSSI Localization: Alternate Systems

Therefore, it is reasonable to conclude that this particular mapping/fingerprinting technique is not fit for purpose as currently described. In addition, their system makes use of expensive isotropic antennae to improve resolution, and relies in each iteration upon a controlled environment for accuracy, neither of which would be suited to a low-cost every-day scenario. RSSI Distribution Based Localization (RDL) (Liu et al., 2012) investigates the properties of 802.11 RF propagation to create an effective localization model, addressing issues #1 and #2 in the work of (Youssef et al. (2007). RDL was conceived based upon the observation that effective DFPL systems to that point all required a dense deployment of sensing nodes. Given that it is desirable to minimise cost, dense deployment will often be unfeasible. Therefore they first investigated the effect of human obstruction on RSSI, to determine how best to deploy resources for detection. They found that the propagation of an obstructed signal path can be modelled in terms of diffraction, with two conclusions. Firstly, that symmetrical obstructions are of equal effect – that is to say, if an obstruction occurs at a certain distance from the perpendicular line bisecting the path between two transceivers, and so long as the obstruction is in either symmetrical position across that line, the perturbation is of equal effect regardless of which side of the central the obstruction resides. Secondly, that the signal path at the location of an obstruction can be described as a series of Fresnel zones on a plane perpendicular to the shortest path of the signal. Furthermore, they found that obstructions outside of the central Fresnel zone have minimal effect upon RSSI, so long as at least 55% of the central zone is not occluded. Varying position within the signal path therefore can be said to influence RSSI proportional to the number of Fresnel zones occluded, which describes how the variation in RSSI of an obstructed signal occurs, and with the majority of this variation occurring when the majority of the shortest path of the signal is occluded. This explains why a single link is not sufficient to perform localization – not only is the scanning area small, but also the effects of occlusion are symmetrical. Therefore, they conclude that multiple links are required, and that this number grows as the sensor area increases. However, since they are able to quantify the sensor density appropriate to the desired coverage, they were able to minimise the hardware requirements while optimising the sensor placement configuration. With this, they gather RSSI data, model the possible paths of obstruction detection between the links, and then estimate the target's position on each relevant path using Bayesian classification. With this system they were able to produce a localization accuracy of around 70% using a 1m error tolerance, rising to around 85% if the tolerance is set to 2m. However, their approach does not address multiple occupancy.

Deak et al. (2012) take a very different approach to localisation to address this problem. In their experimental setup, they use a much smaller sensor area than in other implementations, only ~10m squared, surrounded by 10 wireless nodes in bidirectional mode. This relates to the increased difficulty of detecting multiple as opposed to single occupancy. Then, after recording RSSI data, they prune the dataset to remove node links which show the least variance in testing, and use a multilayer Perceptron neural network to classify the data into three sets – occupancy in one half of the sensor area, occupancy in the other half, and occupancy in both. After training the network and validating its performance, their system was able to correctly identify each of the three classes with ~90% accuracy.

It can be seen that RSSI based localization in the passive mode can produce accuracy comparable to that of the active mode, and that multiple approaches have been attempted in order to address the weaknesses inherent to inference of position data from transmission in the RF medium. Also it is evident that no single approach adequately addresses these weaknesses to the extent that would allow employment of this technology for robust human localization in a real world setting. However, the differences in approach, both algorithmically and structurally, are not in every case obviously mutually exclusive. It is therefore hypothesized that a combination of elements from the more successful implementations described could potentially allow the creation of a system that could perform localization with sufficient accuracy for use in the detection of cases in which two persons are within a certain distance of each other, and from there to infer human interaction by further means.

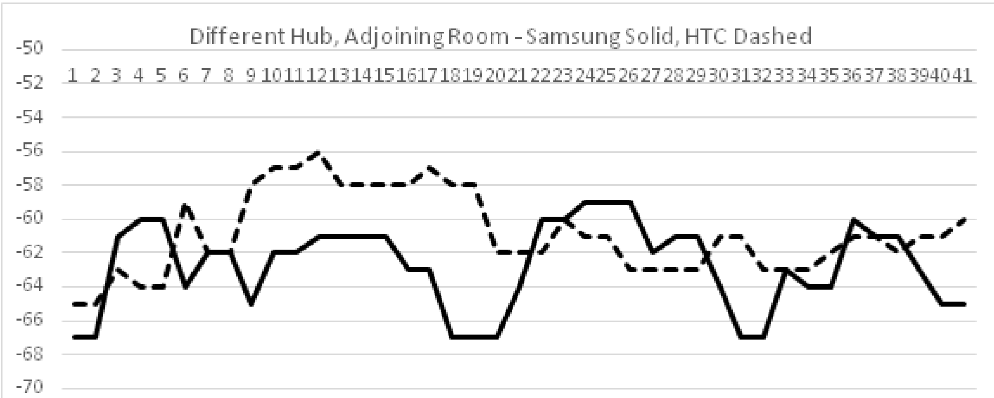
3. EVALUATION

We constructed a testbed where the sensing devices are placed in groups of no less than two, such that one lies at the end point of a line between the person and the nearest Wi-Fi hub, and that the second lies at the end point of a line between the Wi-Fi hub and the likely position of another person.

3.1. Design

The system collects RSSI data for each packet received and classifies which RSSI perturbations indicate the presence of a person in the sensing area. It uses these perturbations to locate the person present and is able to distinguish between multiple persons within the sensor area. It can determine the proximity of persons in the case of multiple occupancy and activates the mobile device microphone when proximity is within a certain range. It also detects whether the audio recorded contains speech and uses the combination of proximity and detected speech to classify incidences of human interaction. Finally, it displays these incidences in a human-readable way. The phones were Samsung Galaxy S2 running Android 4.0.3 and HTC One Mini 2s running

Figure 1. Data recording process flow



Android 4.4.2. The 802.11 Wi-Fi access points were BT Home Hub 3 and Sky Hub SR101. The data recording process is shown in Figure 1.

The system uses Bayesian classification for localization and detection of multiple occupancy, with inspection of multiple occupancy/recorded audio pairs conducted using Bayes. Matlab's pattern recognition tool was used for classification of interaction events.

3.2. Results

Tests were carried out corresponding to the test plans shown in Figure 2, Figure 3 & Figure 4. In each case, the devices oriented face up on flat surfaces with their bottom edge towards the hub.

In the graph plotted from each set of test results (Figure 5), the solid line represents the ambient volume, plotted against the right axis, and the dotted line represents the RSSI level, plotted against the left axis. Each tick on the horizontal axis represents two seconds.

In this test, the room is quiet to begin, and no persons are present in the testing areas (see Figure 2). From tick 5 to tick 20, a person is seated in the left testing area. From tick 20 to tick 35 a person is seated in the right testing area. As can be seen from the dotted line, there is no appreciable deviation in the trend during these periods, whereas the expectation would be to see

Figure 2. Test 1 – Chairs One Metre from Device

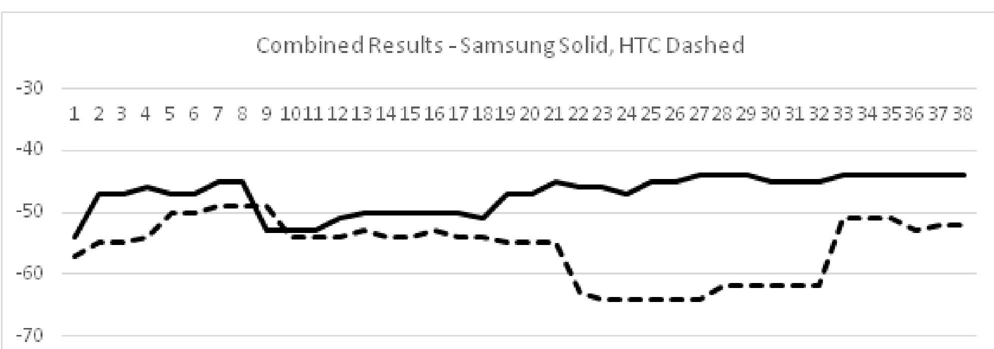


Figure 3. Test 2 – Chairs 0.5 Metres from Device

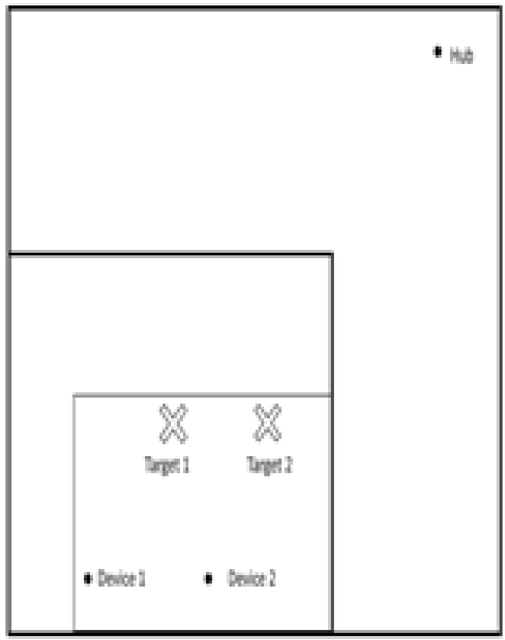


Figure 4. Tests 3 & 4 – Targets 0.5m from Device – Hub in Adjoining Room

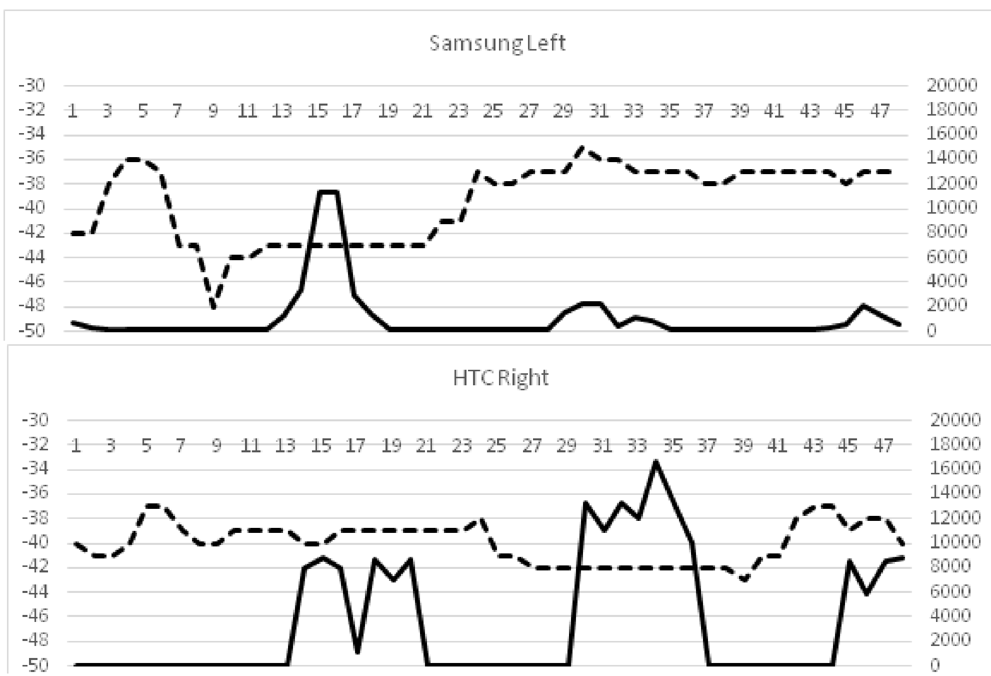


Figure 5. Test 1 – Same room, persons present 1m from device

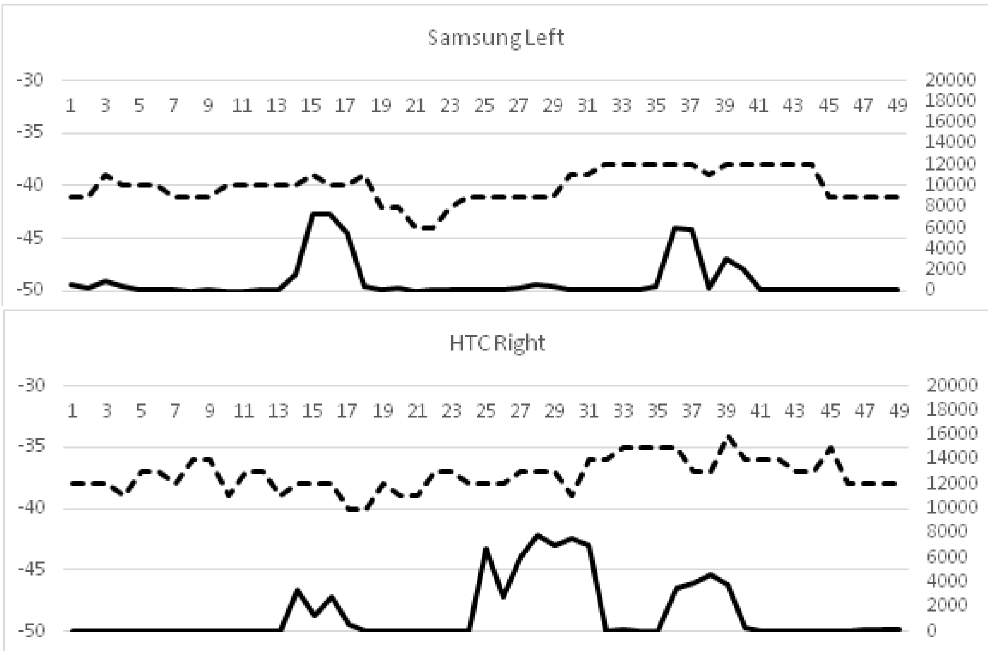


Figure 6. Test Two – Same room, persons present 0.5m from device

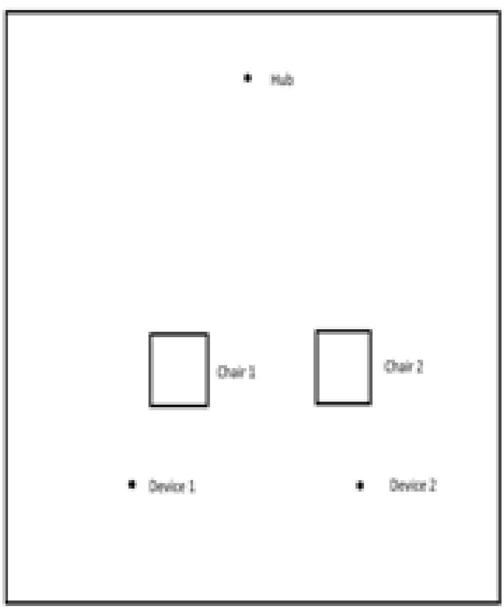
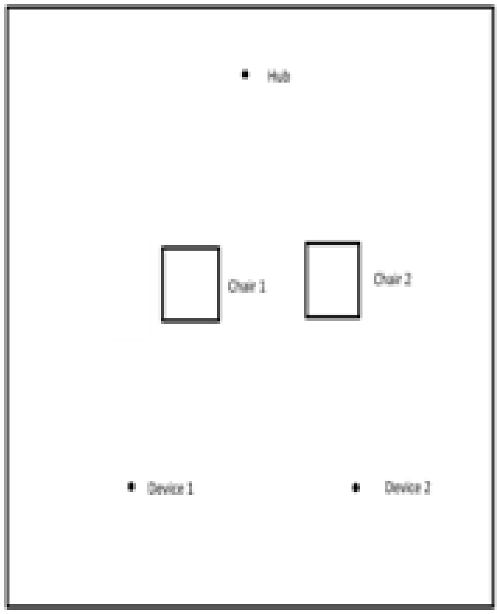


Figure 7. Test Three – Adjoining room, persons 0.5m from device



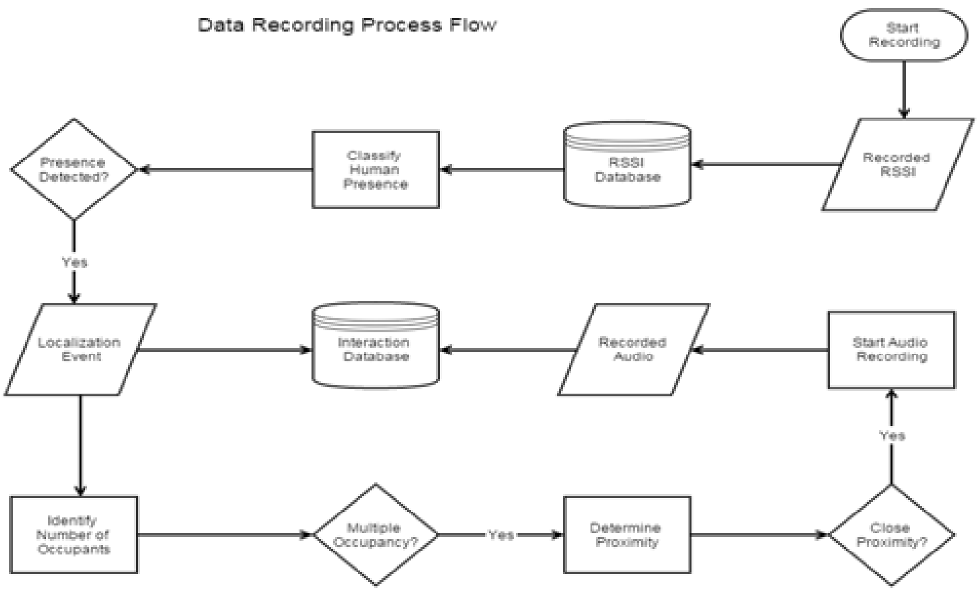
a decrease in RSSI during these periods. Indeed, the trend in the HTC device is marginally in the opposite direction to that which is predicted.

The solid line represents audio levels – for ten seconds during each seated period, the test subject spoke in the direction of the device they were seated beside. This shows that at least this portion of the test showed a positive result, with the proviso that the Samsung microphone was found to be highly directional – during the period that the subject was seated next to, and speaking towards, the HTC, the Samsung registered no variance from the ambient level. Finally, at the end of the test, the subject moved away from both test areas, and spoke towards a point between each device – in this, the results show a corresponding peak.

This test was carried out in exactly the same way as the first test, with the only difference being the distance between subject and device is reduced to 0.5m (see Figure 3). In this experiment the decrease in RSSI values between 5 and 20 for Left, and between 20 and 35 for Right, is now noticeable. It is far more pronounced in the older Samsung device, which at first seems surprising, but on reflection, it perhaps implies a more direction-sensitive antenna in the older device, which is in itself a somewhat useful result. Again, the audio data shows correlation, again with pronounced directionality suggested by the Samsung device. However, there is a point of some concern – the audio peak in the HTC device is substantially delayed. Although the test audio timings were not absolutely rigorous, the HTC data has an onset delay in the order of 10 seconds. One possible explanation for this is that there is an issue with how audio buffering is handled.

The next tests were carried out with the hub located in an adjoining room (see Figure 4). In Figure 7, heavy lines represent walls or closed doors. The finer line represents the outline of a bed, with the targets representing positions for seated figures. Since the audio portion has been shown to work (with some reservations) further relation of testing results in differing environ-

Figure 8. Test Four – As test three but with different hub



ments seemed unnecessary, since audio volume is only minimally affected by such circumstances. Therefore, both sets of RSSI results are shown in a single graph (see Figure 7).

Given the awkwardness of moving in a more confined environment, the timings were changed slightly, with a person present in the target corresponding to the solid Samsung line between tick 8 and tick 20, and present in the area corresponding to the dashed HTC line between tick 20 and tick 32. These tick values were established by making note of the changes in the on screen RSSI values when in proximity to each device, and then locating the corresponding data points in the recorded data. It can be seen that in this case the overall RSSI levels are decreased in the unobstructed state by approximately 10dBm on average, but that otherwise the response appears somewhat the same as in the same-room scenario, with two noticeable differences. Firstly, the response from the HTC is far more pronounced. The phone orientations remain the same, face up on a flat surface with the bottom edge pointed towards the hub. Therefore it seems strange that the results should be reversed, since in the previous test the Samsung was more sensitive. One possible explanation for this is the multipath effect. The second noticeable difference supports this to some extent – attenuation of the HTC signal begins when the subject is proximate to the Samsung device, despite this leaving the imaginary direct line between HTC and hub unobstructed. This may also be supported by the suggested increased directionality of the Samsung device. Given that the HTC may be more receptive to incoming wave paths which deviate from its axis, an obstacle to a reflected ray coming in at a non-axial path would have a greater effect on the reported RSSI. It does not however explain why the overall sensor drop in the HTC is so much more pronounced. That the overall result should be the reverse of the case in the prior experiment has been discussed, but there is no readily apparent explanation for the greatly increased magnitude of effect. In the same room experiment at 0.5m range from the device the drop was in the region of ~5dBm from the resting state, whereas in the adjoining room it is ~10dBm, which given that it is a logarithmic scale implies a much greater proportional attenuation.

One final test (see Figure 8) was carried out using the same test parameters as test three, except with a Sky Hub SR101, rather than the BT Home Hub 3.0 used in all other tests. Unfortunately test conditions besides this were not ideally controlled, as it was not possible to bring the Sky Hub to the same test environment – however, it was arranged as closely to the previous test as possible, with objects lying in the same relation to each other and carried out in the same format. Therefore the data is only weakly suggestive. From tick 5 to tick 20, a subject was proximate to the Samsung device. From tick 20 to tick 35, a subject was proximate to the HTC device. Some correlation is visible in these segments, with a greater response in the Samsung device this time, and much greater overall variability in the recorded values. It is impossible to say given imperfect conditions what this means – the only conclusion that can be drawn is that some response will be present when using a different hub and a different environment.

4. CONCLUSION

Results show that in certain conditions, the presence of a person in close proximity to a mobile device at a point intersecting a line between the device and a connected hub produces a measureable decrease in RSSI levels. When this is combined with collection of amplitude maxima from device microphones, it can be used to infer social interaction in these specific conditions. If we accept the combination of human proximity and an increase in ambient noise amplitude maxima as a valid metric for detecting human interaction, then our research suggests that the addition of a sound sensing component to such a system would be valuable. A future system using Bayesian inference may allow for detection of human presence at much greater ranges, since the limitation of "fingerprinting" results (that they test for presence at specific locations rather than directly inferring position from data) could be relaxed if the parameters of such inference were limited to detection of presence only rather than localisation.

We did find variability in the sensing behaviour of different devices, and in the propagation characteristics of different hubs. This on the one hand presents a challenge to anyone attempting to create a system based on the basic assumption that anyone trying to create an ad-hoc low cost sensing network of this type will have to make do with whatever hubs and devices are available at hand, since the fidelity of any results would be uncertain until tested on-site. On the other hand, it does suggest a possible improvement given a more selective approach to hardware. There is likely to be a class of low cost mobile devices that returns human presence correlated RSSI data with high fidelity for a given test setting. There is likewise likely to be a class of low cost consumer Wi-Fi hub that exhibits "useful" Wi-Fi propagation characteristics in a like variety of test settings.

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