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A hybrid Passive & Active Location Aware Framework for Tracking movement indoors

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***Abstract* – There are various technologies that can be used to track people indoors. Several benefits exist both in healthcare, commercial, policing and other sectors for being able to keep track of people in various locations. There exists a variety of technologies which enable the tracking of people and objects inside. Like all technologies, there are trade-offs in regards to privacy, costs, accuracy in many of these. We provide a framework which can work with a number of wireless systems to provide aactivity monitoring in home environments. Monitoring people at home can provide an understanding of activities that persons are engaged in. These activities can be classified with either active or passive localisation technology. This paper provides an overview of an wireless location framework which allows the plugging in of multiple active tracking solutions such as beacons in addition to interacting with passive localisation techniques to track people inside and also categorize their activities.**

Keywords: Movement Detection, Device Free Passive Localisation, Presence Detection, smart phone activity detection

1. INTRODUCTION

Indoor location determination has become an important service in so far as it can track the movement of people indoors whether in the home or in shopping malls (Deak et al., 2010). Current implementations of location intelligence (via LAS) in a Mobile environment suffer from several issues and the choice of which technology to make use of is critical. Location tracking techniques can be divided into two main categories - active localisation and passive localisation. The distinguishing factor is the participation of the tracked individual. In a passive system, the user is not required to participate, i.e. the system can track them without any need for an electronic device to be carried or attached which sends out signals to help deduce their location. In an active system, an electronic device is carried. A significant drawback of many indoor locating technologies is the requirement to deploy a costly and complex infrastructure composed of dedicated hardware. The existing IEEE 802.11 networks and support for wireless protocols by the clear majority of mobile devices makes Wi-Fi a logical choice for low-cost indoor location detection. Wireless networks are capable of tracking movement through the network using a technique known as radio mapping or more commonly fingerprinting, which most IEEE 802.11 based location detection approaches are based on. Fingerprinting requires a complex setup or training phase to construct a map of pre-recorded received signal strengths (RSS) from nearby access points (AP's) at every position of an interesting area (Carlin & Curran, 2014). The results are stored in a fingerprint database which can be queried with any RSS to identify and map corresponding locations. This fingerprint database or radio map can be used to create a model. Fingerprinting provides good accuracy but is highly vulnerable to environmental changes such as rearranging furniture or moving the APs. One method of reducing this factor is collaborative feedback allowing a continually evolving radio map however the variation in RSS generated by different Wi-Fi chips could be a significant limitation in using a Wi-Fi based approach. An important consideration is that the decisions made when installing a wireless access point were generally to catch large congregations of users and primarily to provide the highest available throughput to those users. Indoor environments are also especially noisy with other radio devices like wireless headsets and microwave ovens causing unpredictable interference. These factors result in a coverage area which is less than ideal for fingerprinting. Fingerprinting can be divided into deterministic and probabilistic approaches. There are many models within each category each with their own pros and cons, overall the probabilistic models are the most promising with the most notable being the Bayesian-Hidden Markov model.

There are several techniques available to identify and track a person's location. Bluetooth low energy beacons are fast becoming an attractive choice for an indoor location determination system since BLE beacons provide excellent accuracy and precision. Either Wi-Fi or beacons are the most appropriate choices for an accurate and reliable indoor tracking system. GPS is unsuitable indoors and RFID is too costly, complex and does not provide the equivalent accuracy of Wi-Fi or BLE beacons. Wi-Fi has good precision with low cost but is usually complex to implement. BLE beacons on the other hand are much easier to implement, provide excellent accuracy and precision and are very cost effective given the prevalence of Bluetooth devices.

This paper outlines an extensible indoor location tracking system which uses Bluetooth beacons to locate individuals indoors. The framework has been designed to work with other tracking technologies such as WiFi as well. It also employs device free passive localisation (DFpL to classify activities whenever the person being tracked is not moving around with their mobile device. The system is deployed on a mobile phone (Android) and there is a web service for administrators which allows the addition of rooms, beacons and activities. The core concepts used to locate a person using passive techniques are explained in the next section which is then followed by a review of our location detection Locator framework which may be used to implement an indoor tracking solution for determining locations and activities (Curran & Norrby, 2009).

2. DEVICE FREE PASSIVE LOCALISATION

Device Free Passive Localisation (DfPL) is tracking human subjects when they are carrying no electronic devices in the localisation aspect. This can work as the human body causes a noticeable distortion to the wireless medium (unless the environment is very 'noisy') (Furey et al., 2011a). Location tracking techniques for active localisation require tracked personnel to participate actively however passive localisation is based on monitoring changes of characteristics dependent on people's presence in an environment. There is a challenge with deploying Device-free Passive Localisation (DfPL) systems as people will not be actually carrying a device which helps track movement but rather a nearby wireless access point must determine movement above a pre-determined threshold and correctly classify it as moving/non-moving (Furey et al., 2008b; Curran et al., 2011).

DfPL is where variances of the signal strength in a wireless network are monitored. The human body contains about 70% water and the resonance frequency of water is 2.4 GHz (Deak et al., 2013). The frequency of the many commercial and home wireless networks is 2.4GHZ, so a human will behave as an absorber thus attenuating the signal (Vance et al., 2010; Vance et al., 2011). A system to overcome these problems was HABITS (Curran et al., 2007). It used artificial intelligence methods working on movement history patterns to gain higher levels of position accuracy. The premise was to record users walking trails over time inside in order to predict the most likely paths that they would travel in the future thus overcoming radio frequency signal black spots where other systems failed. This would allow more accurate real time monitoring. This individual DFPL identification led to further investigation into the problem of identifying multiple people in a room using simply RSSI measurements and the application of smoothing algorithms to filter the RSSI recordings (Furey et al., 2008a). Previous work done at Ulster University was testing the accuracy and robustness of indoor location detection in the field of robotics (Curran et al., 2009) and consultancy for industries connected to tracking hospital patient records and tracking people in shopping malls. Another project improved the accuracy of 802.11 WiFi location sensing systems by combining the strength of WiFi signals and the user activity recognized from accelerometer data (Furey et al., 2010a; Furey et al., 2010b). This concentrated on recognizing basic activities from accelerometer data, such as standing still and climbing upstairs with the output of the activity recognition then fed into the existing WiFi location sensing system to improve the accuracy of the estimation of the user's location.

2.1 Device Free Passive Localisation on Mobile Phones

Nearby movement can be detected using mobile phones where software on the phone detects variations in the received signal power thereby allowing decisions to be made on whether a person is moving near the mobile phone (Deak et al., 2014). This opens the possibility of a multitude of applications making use of knowledge which can determine if a person is moving in the vicinity. This idea can also be transferred to other wireless devices such as laptops but the mobile phone is the more obvious candidate. At present the only way to determine human presence in a room equipped with a mobile phone would be to run some application which works through the camera on the phone. This would be a heavy drain on the phone battery as image processing is intensive. The camera on the phone also must be orientated in a certain way and would only have a specific viewpoint. The other option might be sound recognition but this is processor intensive and prone to repeated failure should the person(s) speak no words. The mobile phone detects variations in the strength of the wireless signal received at the device and uses these variations to determine movement of a person. The device detects variations in the amplitude of the signal. For example, the device may detect the Received Signal Strength Indicator values for the wireless signal and monitor how these vary. Movement may be determined to have occurred when the detected RSSI amplitude varies above a first threshold and/or below a second threshold. Motion is only determined to have occurred if the amplitude of the RSSI values rises above the first threshold and/or falls below the second threshold a predetermined number of times in a predetermined duration of time. This technique identifies movement without the need for the person to speak. Using mobile phones in a 'device-free technique' is different in that we are not attempting to 'track' an individual from a remote location but rather apply the principles of radio interference through the presence of a human so that a nearby phone can track the movement of a person for all manner of alerts and subsequent actions. Here the mobile phone is the 'access point' and the device which detects movement. This would allow app developers to incorporate this unique technique of detecting movement into their existing apps. One simplistic example could be alarm clock apps which detect the person being awake and moving in the room and thus cease to sound the alarm tone. This technique is also useful in allowing a mobile to 'be ready' as it detects movement e.g. screen of the mobile phone may turn on if movement is detected. The phone does not need to be docked and the threshold of detection can be adjusted so that disturbances by animals do not lead to false positives. The resolution of detection is room level ideally at less than 1 meter (Furey et al., 2011b; Furey et al., 2011c).

Currently, there are a limited number of means for a mobile device to detect the presence of a person nearby. One method is to use the phones camera. Thus, movement detection can be achieved by running a software application that receives images from the camera of the phone. However, this technique requires image processing and therefore demands a significant amount of power, which drains the battery on the phone relatively quickly. The camera on the phone must also be orientated in the optimum direction and even then, it only provides a specific viewpoint. The nearest competitors therefore are around camera based motion detection. One such popular app for Android is called Motion Detector Pro which is a surveillance application that uses the camera to sense movements in the area and send a message with a photo to others. Yawcam is another motion-sensing security app which uses the phones camera to detect movement. It is enhanced with features which allow the usual automatic uploading, emailing, or just saving captured images. Other apps include motion detector (BFrontier), MySnapCam, Motion Detection Alarm (DevDroisSP) and inView (Shenzhen Corp). There are iPhone apps which simply detect movement through the iPhones accelerometer and can sound out warnings such as "Back away from my iPhone". One example is Motion Alarm (Maplewoods Associated Ltd). Similar apps exist for other mobile platforms as well but they have limited usage and solely rely on the phone moving. Another option for the detection of a person using a phone is sound recognition. Again, this requires intensive processing and would also be prone to failure should the level of noise created by the person be too low to detect effectively.

Therefore, a DfPL solution is a much-improved method of detecting human motion using a portable electronic device. The WiFi is generally turned on and sensing internal networks. There is little overhead in the detection of movement using our unique technique. It is also less intrusive than camera based detection techniques. Future applications of detecting movement could be around gaming where movement plays a part or apps which can be used for finding a smartphone or preventing phone theft. If movement is detected, an app can be directed to take a picture and send it to others. This can also be used for watching a business/home or keeping an eye on pets. The images could also be stored on the cloud or locally on the phone (Furey et al., 2011d).

A DfPL mobile phone technique is also useful in a broader sense. For instance, it can be used to get the mobile phone 'ready' as it detects movement nearby. For example, the phone may change from a standby mode where it is running on low power and performance to an active mode where it is running on higher power and performance such that it is ready to be used by a user. An example is that the screen of the mobile phone may turn on if movement is detected. Another application is to turn off an alarm that is sounding if movement is detected nearby. For example, a wake-up alarm may be sounding and movement of the person woken by the alarm may deactivate the alarm without the person having to go to the phone, pick it up and switch the alarm off. The present invention is particularly advantageous with phones and smart phones since they are so widely used and software may be readily downloaded to convert the phone or smart phone into a motion detector. Similarly, a myriad of software applications that can use the motion detection software may be readily downloaded to the phone or smart phone. Although the present invention is beneficial to smart phones, less preferred embodiments are also contemplated wherein other portable electronic devices may be used such as a laptop. Other potential applications reside in the healthcare domain where a mobile phone can be used to detect movement of patients and in some cases, form an alert system. There are several areas where movement detection on existing off-the-shelf smart phones can lead to inexpensive solution for remote monitoring.

3. BLUETOOTH LOW ENERGY (BLE)

Bluetooth low energy (BLE) is a variation of classic Bluetooth with the aim being to provide an efficient technology for controlling applications where data sent is very low. Examples would include sensor values or control commands. BLE power consumption is reduced to between 50-99% in comparison to standard Bluetooth power consumption. BLE device lifetime powered by a coin cell battery ranges between 2 days and 14 years. This extremely low power consumption is ideal for devices needing to run off a tiny battery for long periods but the ‘power of Bluetooth Low Energy is its ability to work with the billions of existing Bluetooth enabled devices currently on the market. Using Bluetooth for location determination is mainly achievable when many known location stationary devices exist and the trilateration technique is used to determine location.

3.1 BLE protocol

Although the classic Bluetooth and BLE protocol stacks share many common features, BLE includes some significant differences. Similar to Bluetooth classic, the BLE protocol stack has two main parts; which are the controller and host. The link layer and physical layer are part of the controller. The logical link control & application protocol (L2CAP), the attribute protocol (ATT), security manager protocol, generic attribute protocol (GATT) and generic access protocol (GAP) are part of the host. The controller and host communicate through a host controller interface (HCI). The generic access protocol stipulates device roles, management of connection establishment, security and procedures of device discovery. Bluetooth GAP specifies broadcaster, observer, peripheral and central roles. Devices may support many roles but they can only play one role at any time. Application layer functionality not defined by the Bluetooth specification sits on top of the host. The BLE protocol stack is shown in Figure 1.

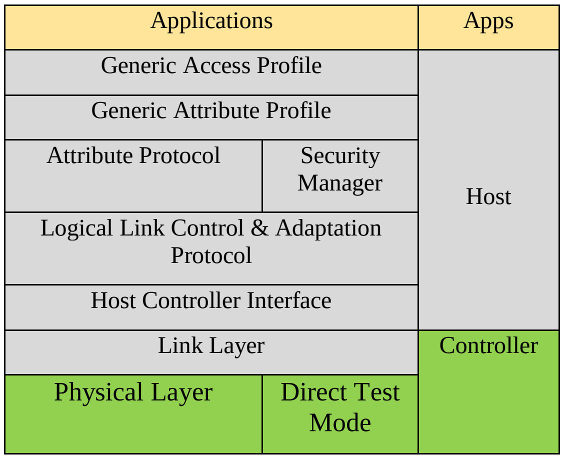

Figure 1: BLE protocol stack

The BLE protocol stack features a smart host control which places intelligence in the controller which allows the host to sleep for longer periods. It also allows it to be woken up by the controller only when needing to wake up. This is one of the primary techniques BLE uses to achieve its low power consumption however the differences in the controller render the BLE controller incompatible with classic Bluetooth controllers. This means that a device which implements BLE cannot communicate with classic Bluetooth device. Many devices implement both protocol stacks and are known as dual-mode devices. Another technique used by BLE to reduce power consumption is the number of frequency channels used for device discovery.

Known as advertising channels classic Bluetooth uses 32 channels which are scanned to determine whether any others are seeking to make a connection. BLE uses 3 channels for this task. This reduction significantly reduces the amount of time required to scan for devices, classic Bluetooth takes 22.5ms to scan while BLE takes 0.6 to 1.2ms. However, this reduction comes at a cost as there is a higher chance that another device is broadcasting on the same signal, interfering with the BLE signal. An overview of the technical differences between classic Bluetooth and BLE is shown in Figure 2.

Technical specification	Classic Bluetooth technology	Bluetooth Smart technology
Distance/range (theoretical max.)	100 m (330 ft)	>100 m (>330 ft)
Over the air data rate	1–3 Mbit/s	125 kbit/s – 2 Mbit/s
Application throughput	0.7–2.1 Mbit/s	0.27 Mbit/s
Active slaves	7	Implementation dependent
Security	56/128-bit and application layer user defined	128-bit AES Counter Mode CBC-MAC & app layer user defined
Power consumption	1W as the reference	0.01–0.50 W
Peak current consumption	<30 mA	<15 mA
Service discovery	Yes	Yes
Profile concept	Yes	Yes

Figure 2: Classic Bluetooth and BLE technical comparison (Source: Wikipedia, 2017)

Any BLE compatible device, such as a smartphone, is able to take on the role of a beacon however the term beacon usually refers to a piece of single purpose dedicated hardware designed to be cheap and with a long lifetime that transmits data in the form of Bluetooth beacon frames. Beacons are broadcast-only, non-connectable devices however they may become connectable (by switching the GAP from broadcaster role to the peripheral role) to allow the beacon to be updated or configured over the air.

4. LOCATOR FRAMEWORK

The systems database stores any long-term application data, including all information relating to locations, positions within rooms and beacon metadata such as assigned positions. The database also holds information relating to application users, activities and position histories (positions which the user has visited). Since this data is generated based on current data, no statistical data needs to be stored. All layers of the web application make use of the open source Spring framework. Spring is an application and inversion of control container for Java web applications which relies heavily on the use of interfaces and XML wiring to inject dependencies (or configurable properties) into other classes. The use of dependency injection is one of the most effective ways of reducing a class' dependency on another class and greatly aides in keeping classes loosely coupled, reusable, extensible and highly testable.

It is evident that there are many techniques available to identify and track a person's location. The problem this research overcomes is the implementation of a system capable of identifying a person's location in an indoor environment combined with determining activities using device free passive localisation techniques. Bluetooth low energy beacons are an attractive choice for an indoor location determination system since BLE beacons provide excellent accuracy and precision. A beacon system is also feasible since its complexity is comparatively low although the system will require use of dedicated BLE beacon devices, they are relatively cheap hardware given the prevalence of Bluetooth devices. Modern mobile devices come equipped with Bluetooth hardware as standard and natively support BLE connections allowing the clear majority of users to immediately make use of the system. When implementing a beacon system a decision needs to be made regarding the broadcasted packet format. Although a new standard, Eddystone usually offers the greatest flexibility and is becoming the preferred approach to implementing a beacon system. Therefore, we adopt the Eddystone frame format. This section outlines the architecture of the systems.

4.1 Architecture

Kontakt smart beacons which support the Eddystone frame format and can broadcast Eddystone-UID are used. The beacons are high performance supporting many features such as simultaneous multi-frame format broadcasting and has an excellent battery life. Given the relatively short range in which beacons work, the transmission power of beacons has been set at low settings allowing the beacons to last for very long periods of time which the apps estimate at 38+ months. The advertising intervals have been set at 100ms to ensure that beacons are read successfully by the mobile application and distances calculated are as accurate as possible. The system database stores any long-term application data, including all information relating to locations, positions within locations (e.g. rooms) and beacon metadata such as assigned positions. The database holds information relating to application users, activities and position histories (positions which the user has visited) (See Figure 3.

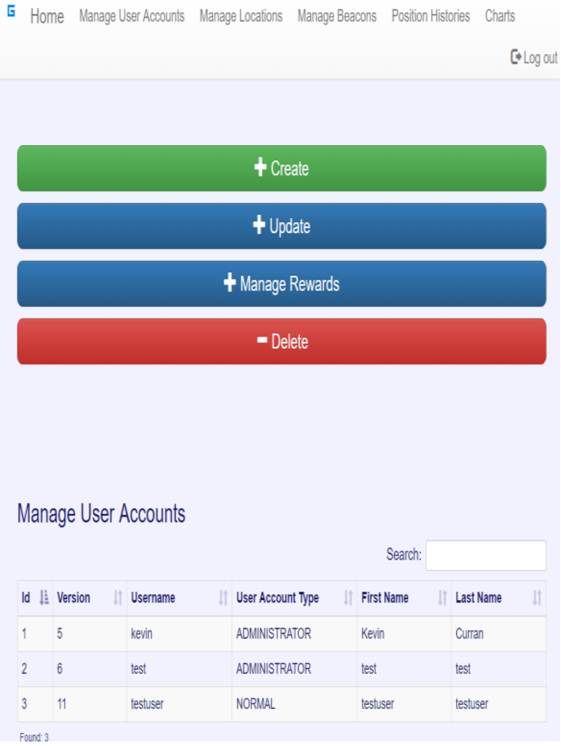

Figure 3: Main Web Application User Accounts page

4.2 Passive Localisation

Our system also can monitor the environment when no movement takes place with the phone. This allows us to classify activities to supplement the active location determination which occurs through the beacons. Indoors, radio frequency (RF) signals bounce around and factors such as curtains, thick walls, people and temperature can each affect the way a signal propagates through the air. The human body also interferes with wireless signals such as coming from a standard household access point. We extend our previous work in detecting human movement by using the mobile phone lying static whilst connected to an off-the-shelf wifi 802.11 access point (Deak et al., 2011) to ascertain movement. The human body has around 70% water which causes variances in the Received Signal Strength Indicator (RSSI) and this disturbance in the signal strength of the wireless communication can be significant. Monitoring changes in the RSSI, one can detect human presence or when the monitoring device is moving. The light green line in Figure 4 shows DfPL in action.

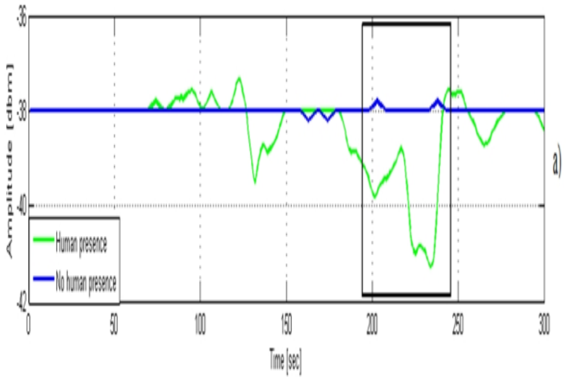

Figure 4: Device Free Passive Localisation picking up human movement

5. EXPERIMENTAL RESULTS

Beacons were deployed in various location with each location having multiple fictional positions (e.g. entrance, sofa) each assigned with a beacon. The admin user can login to the deployed application and configure all beacon data including assigning beacons to specific positions. Figure 5 illustrates this process.

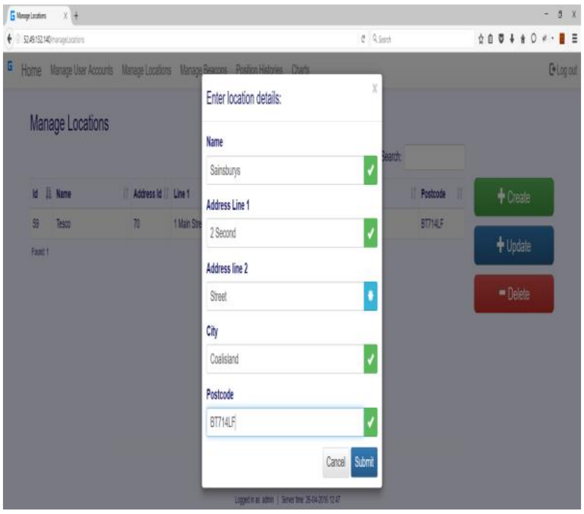

Figure 5: Entering new location details

When a user is within range (0.5m for testing) of a beacon they are recorded at that location and position history is saved. The total time spent at each position is recorded. Table 1 shows the positions in testing.

Table 1: Locations visited and activities

Step	Location	Position	Duration	Activity
1	Kitchen	Sink	65 seconds	Standing
2	Kitchen	Fridge	15 seconds	Standing
3	Bathroom	Wash basin	30 seconds	Standing
4	Kitchen	Fridge	20 seconds	Standing
5	Study	Sofa	90 seconds	Sitting
6	Study	Sofa	10 seconds	Standing
7	Kitchen	Sink	40 seconds	Standing
8	Bathroom	Wash basin	45 seconds	Sitting
9	Study	Sofa	100 seconds	Sitting

The user's activity display is updated at each stage indicating that position histories were successfully being saved. The position history is shown in Figure 6 within the app and Figure 7 shows locations on the web application.

Figure 6: Position histories

The device free passive localisation aspect is invoked when no movement is detected within 60 seconds. The phones RSSI values are probed to ascertain whether the person is moving or staying still. There are only two activity classifications in the system but this can be expanded to determine other activities such as washing, exercising or sweeping in the future. Figure 7 shows the position histories recorded for testuser4 when moving between locations.

Id	Timestamp	Location	Position	Username	Beacon Instance Id
54	2/18/2017, 9:59:24 PM	Kitchen	Kitchen	j	da0130c45dc1
53	2/18/2017, 9:59:18 PM	Office	3	j	d0bc5cbdbe6f
52	2/18/2017, 9:58:30 PM	Kitchen	Kitchen	j	da0130c45dc1
51	2/18/2017, 9:57:30 PM	Kitchen	Kitchen	j	da0130c45dc1
50	2/18/2017, 9:57:24 PM	Office	3	j	d0bc5cbdbe6f
49	2/18/2017, 9:57:12 PM	Sitting Room	Sittingroom	j	58324d4d716b
48	2/18/2017, 9:57:06 PM	Office	Office	j	583353696b53
47	2/18/2017, 9:55:07 PM	Kitchen	Kitchen	j	704951614c75
46	2/18/2017, 9:54:06 PM	Kitchen	Kitchen	j	704951614c75
45	2/18/2017, 9:53:00 PM	KitchenPurple	Kitchen	j	704951614c75
44	2/18/2017, 9:52:00 PM	OfficeBlue	Office	j	583353696b53
43	2/18/2017, 9:51:30 PM	KitchenPurple	Kitchen	j	704951614c75

Figure 7: Position histories displayed in web portal for testuser4

The device free passive localisation technique can compliment the determination of which room a user was in. We use Received Signal Strength Indicators (RSSI) to give us a relative measurement of the received signal strength at the device and apply probabilistic smoothing and prediction techniques to overcome the noise in the signal. Here the mobile phone is the 'access point' and the device which detects movement. This supplements the active mode of determining which room the person is in and gives us more details on activities.

6. CONCLUSION

There are numerous location determination technologies with advantages and disadvantages associated with each (Feng & Curran, 2009). We outlined a passive/active hybrid system, with a mobile device being carried inside a house and pinpointing the user in accordance with various Beacons located throughout recording locations. Our system provides both a mobile and web based component. Bluetooth beacon technology is a cost-effective means of tracking people indoors. Our framework integrates passive (device free passive localisation) modes of tracking activities so after a set period of time when no more transit between beacons occurs and the mobile phone is static, the phone turns into passive mode and monitors for nearby movement in order to attempt to ascertain whether the person is carrying out an activity. This results in a unique hybrid combining both passive & active modes of tracking.

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