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An Indoor Localisation and Motion Monitoring System to Determine Behavioural Activity in Dementia Afflicted Patients in Aged Care

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Abstract
Dementia is highly prevalent among the older population. Most patients with dementia are admitted to an aged care facility due to wandering behaviour which tends to result in dangerous scenarios such as straying away from the facility and being seriously injured. Due to the decreasing availability of carers in aged care, there is a need to prioritise monitoring of patients that have a severe case of wondering. The challenge is to allow carers to monitor the status of such patients in terms of position localisation and motion behavioural status, in real-time. The long term behavioural analysis of such patients would allow carers to better manage such patients. Current indoor localisation technologies cannot provide the accuracy of location and motion to enable unobtrusive behavioural analysis. Our aim was to develop an indoor localisation and activity monitoring system for aged care workers to aid the prioritisation of surveillance to the patients with dementia. Our system used Radio Frequency tracking combined with motion and heading sensors to track a person. The motion and heading sensor information were incorporated into a human activity classification model to determine the characteristics of a patient's walking activity. We conducted a month-long trial of our localisation network and activity monitoring system in an aged care facility.

Keywords: Aged Care; Localisation; E-Health; Wireless Sensor Networks

1 Introduction

Dementia is highly prevalent amongst the older population. Most patients with severe dementia are susceptible to wandering behaviour, which can result in dangerous scenarios such as straying away from home and being seriously injured. These patients are often admitted to an aged care facility in order to better manage their care. Due to the decreasing rate of carers in aged care, there is a need to prioritise monitoring of patients that exhibit wandering behaviour. The challenge is to allow carers to monitor the status of such patients in terms of position localisation and motion behavioural status, in real-time. The long-term behavioural analysis of such patients will allow carers to better manage such patients. There are many potential clinical applications of position localisation and motion monitoring systems for aged-care services. One such example is that the a position localisation and monitoring system will allow healthcare staff to better manage patients with dementia by being able to classify 'episodes' displayed by patients. Another example clinical application is the use of pedometer motion information to determine the calorific output of a patient, which can be used for dietary management.

Current indoor localisation technologies cannot provide the accuracy of location and motion to enable unobtrusive behavioural analysis. Previous activity monitoring systems have used video and image surveillance,

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which is quite intrusive and requires expensive infrastructure.

We developed an indoor localisation and motion monitoring system for monitoring and studying the behavioural patterns of wandering of patients with dementia to enable prioritised care by the aged care staff. In our evaluation of the system tracked a person using Radio Frequency (RF) combined with motion sensors. The motions sensors are incorporated into a human activity classification model to determine the characteristics of a patient's activity such as running, walking, postural transition, etc. We conducted a month long trial at an aged care facility using healthcare staff members. The trial involved mapping the motion activity of a staff member as they attended their patients.

The requirements of our indoor localisation and motion monitoring system were to:

- Perform indoor localisation using wireless inertial sensors.
- Record a daily path track over an 8-hour period.
- Use small, unobtrusive mobile nodes that can be worn as a wrist watch.
- Use inertial motion sensors to determine walking/standing activity.
- Determine which room a person was currently in.
- Provide a visual display for users to view current position and path travelled.

The contributions of our paper was the development of a novel wrist worn indoor localisation and motion monitoring system and the evaluation of results from a month long trial with Aged Care healthcare staff.

This paper is organized into 6 sections. Section 2 presents a review of related work. Section 3 discusses the location localisation network implementation. Section 4 describes the Dynamic Position Tracking Model used to determine a user's position. Section 5 presents the findings of testing conducted. Conclusions and further areas of investigation are discussed in Section 6.

2 Related Work

Current indoor wireless localisation research has focused on the Ultra Wide Band (UWB) [1], ultrasonic and GSM [2] platforms. Regulations are not clear for the use of UWB, and ultrasonic location detection still requires the use of RF transceivers. GSM uses existing infrastructure, however accurate position resolution indoors is difficult.

Lamarca et al [3-4] describe the Placelab geophysical location system that allows users to determine their position in an urban environment. Placelab uses the Received Signal Strength Indicators (RSSI) of Wifi hotspots and Global System for Mobile Communications (GSM) broadcast towers to determine a user's position. The Placelab software uses a database of known Wifi hotspots and GSM broadcast towers. The Placelab software can be used with a PDA or laptop with Wifi or GSM connectivity. Localisation accuracy is stated as being less then the Global Positioning System (GPS), with 20-25m using Wifi hotspots and 100 to 150m for GSM broadcast towers. The localisation accuracy of either using Wifi or GSM is considered to be too great and requires the use of good GSM or Wifi coverage, which can be problematic for aged care homes situated in suburban or regional areas that have poor GSM or Wifi coverage.

A classical case of using wireless beacons for navigation is presented in [5]. The active badge project achieved a 5-10m accuracy using infrared. The main drawback of this platform is that it required line of sight between beacons. An extension of the Active Badge Project by Ward et al [6], developed a prototype network of ultrasonic beacons to perform real-time tracking of tagged mobile devices in an office environment. Other ultrasonic location systems such as the Cricket Mote [7] and the system by McCarthy et al [8], describes how a network of ultrasonic beacons using time of flight analysis can determine distance position locations.

Klingbeil et al [10] developed a wireless sensor network for monitoring human motion and position in an indoor environment. Mobile nodes with inertial and heading sensors were worn by a person inside a building. A Monte Carlo based localisation algorithm that used a person's heading, indoor map information and static node positions was developed and tested. Our indoor location tracking system relied on a similar particle filtering process but with a wrist-mounted inertial sensor.

Combined visual and dead-reckoning for position tracking has been used successfully by Torres et al [14], Foxlin et al [15] and Kourogi et al [16] with wearable motion and camera sensors. Chen et al [9] used visual tracking for activity monitoring of aged care patients. As noted in [9], visual tracking may be obtrusive but is effective in capturing motion events such as falls.

3 Indoor Localisation Network

The indoor localisation network used inertial sensors to determine and track a person's position and motion

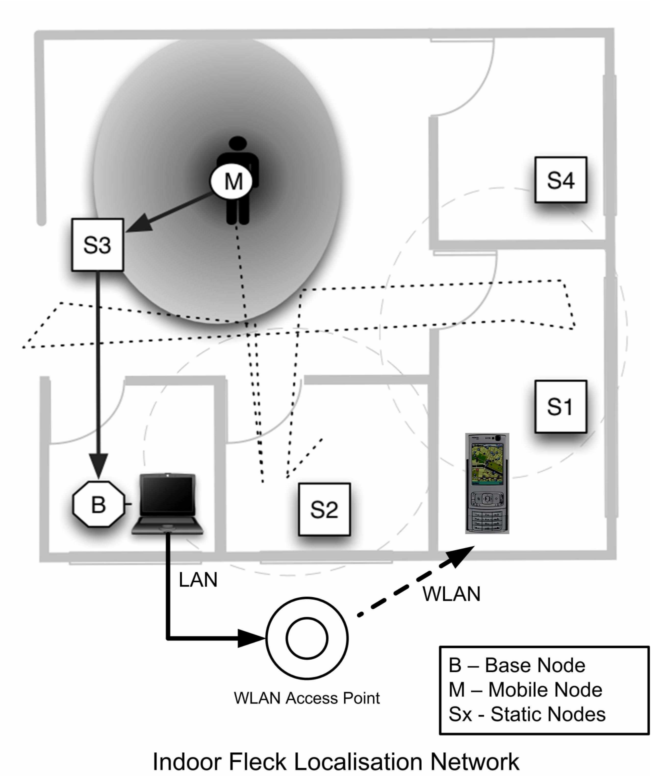

Figure 1: Localisation Network Overview

activity state in an indoor environment. The localisation network, seen in Figure 1, consisted of static nodes placed at known locations within a building. The mobile nodes are carried by users to localise their current position and measure their motion activity i.e. running, falling, etc. The static nodes were used to determine a mobile node's position. The base node displayed the current position of the mobile nodes.

3.1 Static Node

The static nodes, seen in Figure 2, were implemented using the FleckTM-3 wireless sensor platform [11], that has an on-board microcontroller processor and a radio transceiver module for wireless communications. This platform has been used for a variety of wireless sensor applications particularly for environmental monitoring [11]. The static nodes are all connected to the base node via a wireless mesh network employs the multi-hop, network routing communication protocol [12].

3.2 Mobile Node

The Fleck Nano platform is used to implement the mobile node. Figure 3 shows the size of the Fleck Nano sensor (dimension: 25mm x 20mm), compared that of a coin, used for the mobile node. It uses a coin cell battery as a power source. The Fleck Nano's small physical profile and onboard magnetometer accelerometer

Figure 2: Static Node mounted on Wall

is advantageous for clinical applications because it is unobtrusive to the wearer. The mobile node was incorporated within a wristwatch casing, which was worn on the left wrist. Figure 3 shows the Fleck Nano and the wearable case.

3.3 Base Node and Position Server

The base node is also implemented using the FleckTM-3. The base node is connected via a serial connection to a Position Server. The Position Server displays a Floorplan Position Viewer program that shows a building floor-plan with the region the mobile node is currently in, highlighted and also the current motion status of the user. Figure 4 shows the Floorplan Position Viewer.

4 Dynamic Position Tracking Model

The Indoor localisation network uses the Dynamic Position Tracking Model (DPTM) to track the position of the mobile node, in real-time. An overview of the DPTM can be seen in Figure 5. The DPTM used a Particle Filtering estimation algorithm. The model computes the mobile node's position by combining three key pieces of information:

- Proximity of static nodes determined by the mobile node's packet delivery ratio.
- Motion and heading information derived from the onboard inertial sensors.
- Position of the mobile node on the floor-plan.

Particle Filtering [13] uses a set of 'particles' or positions used to determine the location of the mobile node. Each particle represents an estimate of where the mobile may be. The DPTM uses the static-mobile node

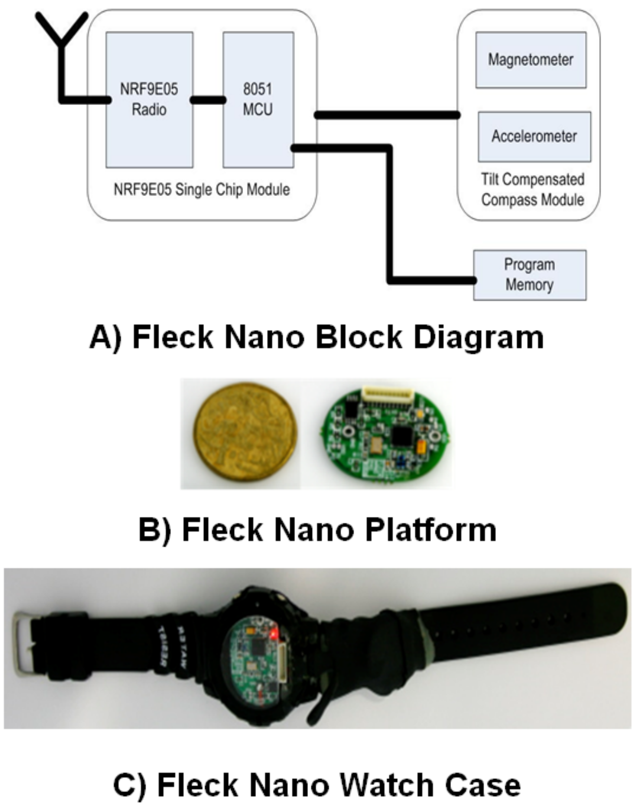

Figure 3: Fleck Nano Platform Overview

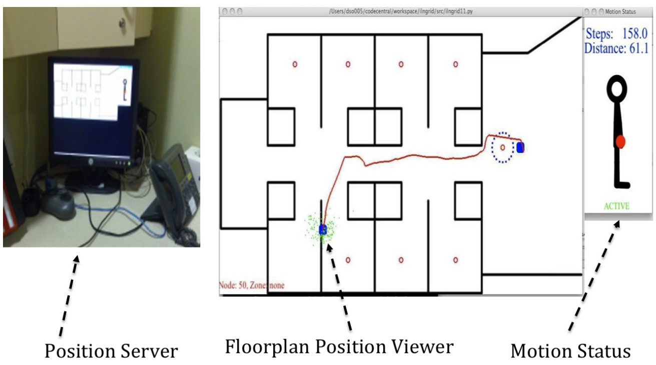

Figure 4: Position Server (Ward Office) and Floorplan Position Viewer

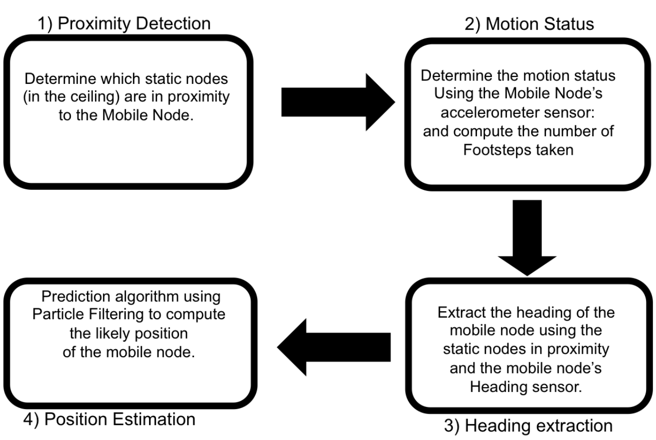

Figure 5: Dynamic Position Tracking Model Overview

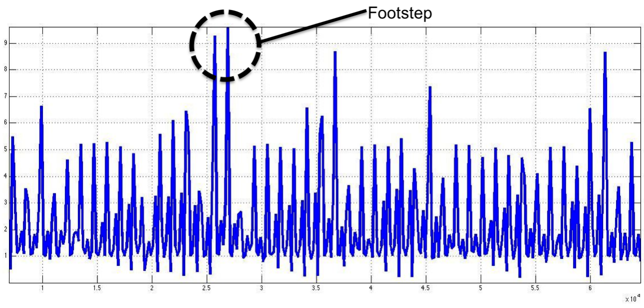

Figure 6: Accelerometer Walking Activity Output

proximity and the mobile node's motion information (acceleration movement and heading) to estimate the next position of each particle.

4.1 Motion and Heading Sensing

The mobile node continuously transmits heading and accelerometer information to the base node. The DPTM uses the accelerometer data to extract when walking motion occurs, in order to calculate the mobile node's displacement from its previous position. Combining the mobile node's calculated displacement and the heading vector allows the DPTM to compute the current position of the mobile node.

4.2 Motion Detection

The mobile node was used to detect the motion of a person. The mobile node had an onboard three-axis accelerometer sensor to detect a person's footstep by measuring the acceleration generated by a foot's heel strike. The signal vector magnitude was calculated using the accelerometer data. An example of the acceleration signal vector magnitude waveform can be seen in Figure 6. The peak magnitude acceleration occurred with a heel strike.

The average person's step length and walking speed is seen in Table 1. These values were derived from walking tests performed using with different adult male subjects. Our results are similar to that reported by Murray et al [14] for adult male subjects.

The footstep displacement algorithm used the Peak-to-Average Ratio of the accelerometer signal vector magnitude to determine when walking motion occurs. A magnitude threshold is then used to determine when a footstep occurs. The threshold does require initial calibration. The Peak to Average Ratio is described by Equation (1) and the Root Mean Square (RMS) is described by Equation (2). The advantage of using the Peak to Average Ratio is that it normalised the accelerometer signal vector magnitude or to remove the gravitational bias of the signal. Accelerometer sensors

Average Step Length	0.8015m
Average Walking Speed	1m/s

Table 1: Step Length and Walking Speed

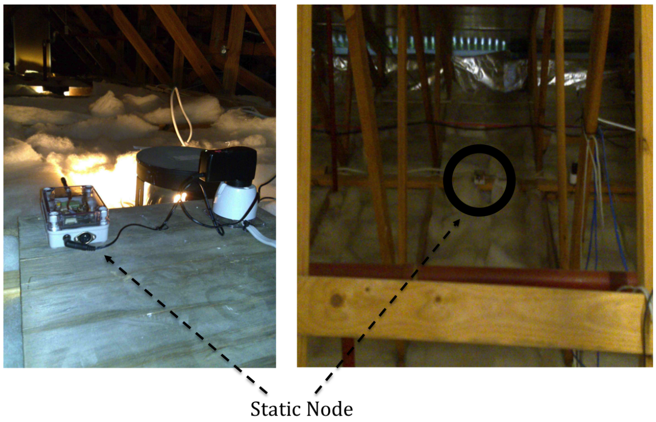

Figure 7: Deployed Static Nodes in Ceiling

have to be calibrated with respect to gravitational bias, as not to affect the magnitude of the X,Y,Z axis signals being measured. The use of the Peak-to-Average ratio allowed the signal vector magnitude and the threshold value to be unbiased from the mobile node's orientation.

$$R(t) = \frac{max(D_t)}{RMS(D_t)} \quad (1)$$

Where R(t) is the Peak to Average Ratio, Dt is the set of acceleration magnitudes over the time interval t, N is the size of the data set Dt and RMS is the Root Mean Square.

$$RMS(D_t) = \sqrt{\frac{1}{N}\sum_{t-1}^{N}(x_i^2 + y_i^2 + z_i^2)} \quad (2)$$

Where x, y, z are the observed acceleration values.

4.3 Hand Motion Interference

Hand motion can distorted the peak acceleration, which causes errors when estimating the footstep displacement. To overcome this, the pitch and roll angles of the mobile node were used to detect if the hand was moving. If the pitch and roll angles exceeded set threshold values, then the footstep displacement algorithm would disregard any detected heel strikes detected.

4.4 Directional Heading

The mobile node has a magnetometer sensor to measure the current heading with respect to magnetic north. The magnetometer was also susceptible to magnetic interference caused by nearby metallic infrastructure. The

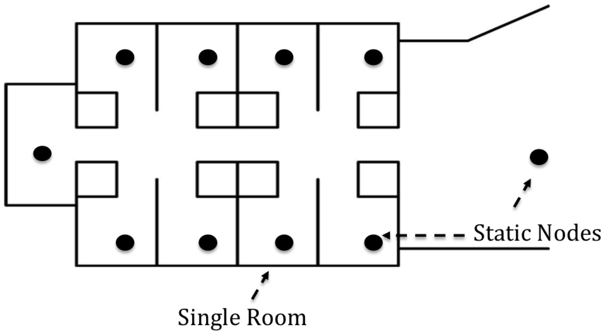

Figure 8: Deployment Floorplan of Static Nodes

DPTM attempts to correct for magnetic interference by using a floor-plan map.

4.5 Floor-Plan Map

The floor-plan map was used by the DPTM to ensure that the mobile node's estimated position was valid. Validity is determined by checking if the mobile node has to move through a wall, in-order to move to its predicted position. If this is found to be the case, then the DPTM will then re-estimate the mobile node's position until it determines that the node's position is in a valid location.

5 Deployment and Trial

The trial was conducted with Aged Care healthcare staff. It was intended that an Aged Care Healthcare worker at the Special Care Unit for Dementia afflicted patients, would wear the mobile node at the beginning of their 8-hour shift. Once their shift for the day ended, the mobile node would be placed in a charging station until the worker began their next shift in the Special Care Unit. No additional setup was required. The data gathered consisted of position and path tracking information, motion information and an interview with the worker about usability. The motion information consisted of footstep and distance walked.

5.1 Deployment

For deployment purposes, the static nodes were placed in the ceiling. Ten static nodes where placed in the ceiling, above each room in the Special Care Unit. Figure 7 shows the placement of the static nodes in the ceiling. Figure 8 shows the placement of the static nodes on the floor plan of the ward. In order to mitigate the effects of

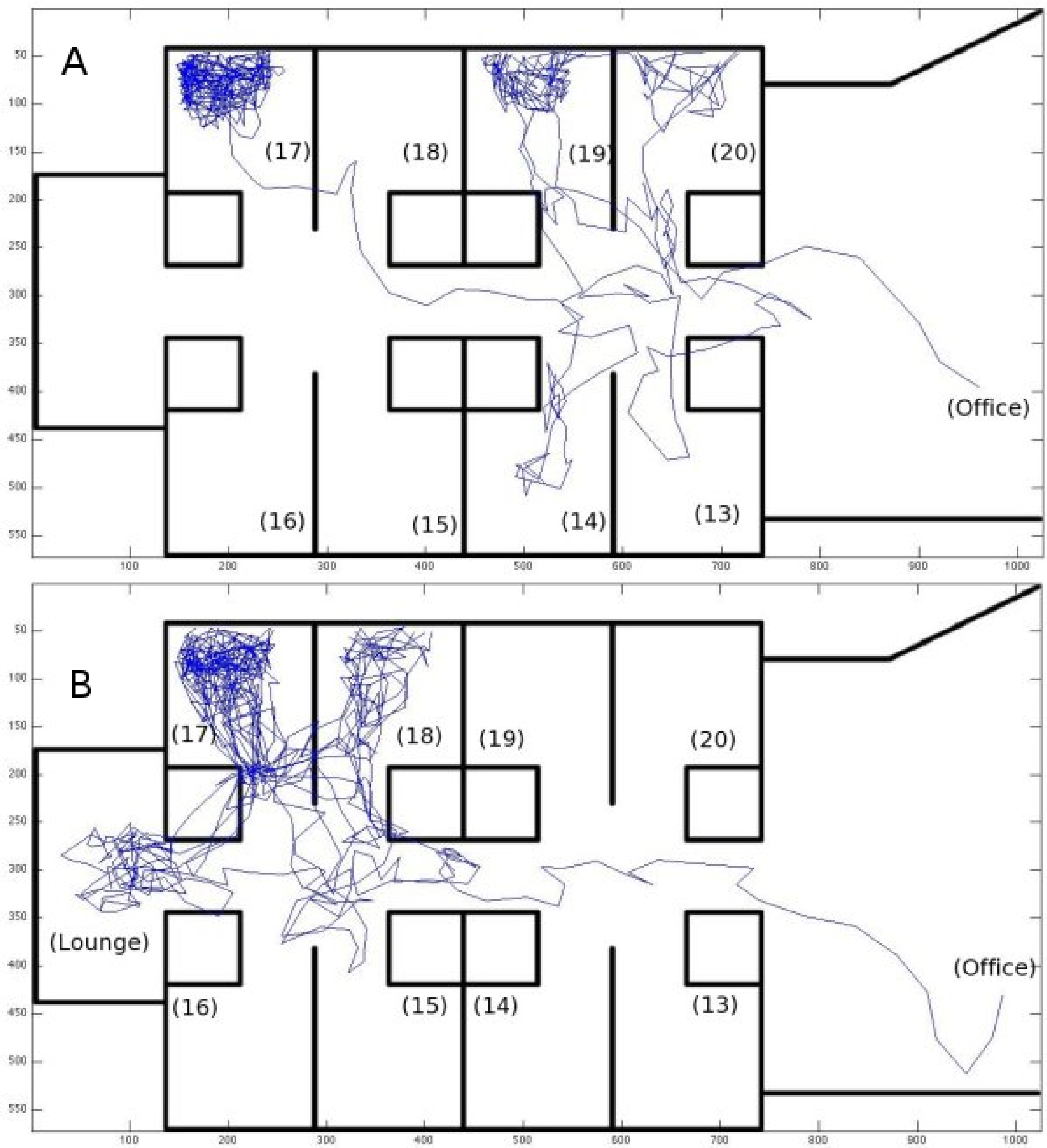

Figure 9: A) Indoor path-track showing the healthcare worker walking from the office to room 20 -> 13 -> 19 ->14 -> 17 B) Indoor path-track showing the healthcare worker walking from the office to room 17 -> 18 ->17 -> 15 -> Lounge ->17

Parameter	Value
Total Distance	10,000m
Total Footsteps	7,000
Maximum Error	3.5m

Table 2: Motion Parameter Status Summary

RF signal interference, the static nodes were placed at specific locations that ensured good connectivity with the mobile node and the base node. These locations were determined by the environment and availability of mains power outlets.

5.2 System Evaluation Results

A subset of the path tracks of the healthcare staff member can be seen in Figure 9 A) and B) showing the path taken by the worker to visit various patients. The path-track in Figure 9 A) shows the healthcare worker walking from the office and visiting the patients in rooms 20, 13, 19, 14 and 17.

The path-track in Figure 9 B) shows the healthcare worker walking from the office and visiting rooms 17, 18 and 15. In addition room 17 is visited twice. The numerous paths taken to the lounge area indicates healthcare staff's attendance to the bed-sheets cart positioned during that period of the day. Significant motion is detected in room 17, as the healthcare worker is physically assisting the patient.

5.3 Motion Observations

The position resolution of the localisation network was found to have a maximum error between 1m and 3.5m. Table 2 provides a summary of amount of detected. The healthcare staff that participated was successfully tracked in the deployment zone.

We found that a maximum error of 3.5 was found to be tolerable as this was equivalent to 2 typical stride lengths. Feedback was obtained via an interview with the healthcare staff involved. Regarding patient usage, it was suggested by the healthcare staff that having the mobile node in a different format such as a pendant, belt or embed in a shoe would be more suitable for some patients.

6 Conclusion and Further Work

We presented a localisation network that tracked people in an indoor environment. The localisation network consisted of static nodes placed at throughout a building. We conducted a trial with healthcare workers at an Aged Care facility. The healthcare workers wore a mobile node to track their current position. We found the position error to range between 1m and 3.5m.

Further work involves investigating how multiple users can be accommodated and how altitude sensors can be used to further improve the human activity classification process. We will also look at developing a mobile phone interface to allow healthcare workers to monitor the position and motion status of users. The main scenario that is envisaged for the mobile phone interface is with healthcare workers to monitor patients remotely, without having to log into a computer to do so. This could potentially allow healthcare workers to better manage patients and their time without having to be physically present.

Further work will also include investigating the integration of GPS with the mobile node to allow for tracking in outdoor areas. The capability to track for both indoor and outdoor environments, provides many advantages by would allowing a more detailed clinical aged care studies of patient behaviour.

The system was able to meet the goals of achieving real-time localisation, recording a path and motion information for 8 hours and using an unobtrusive wearable mobile node. The system was able to achieve reliable localisation with an observed maximum error between 1m and 3.5m. Potential improvement to the system using other types of motion sensors to monitor human movement will enabled better accuracy.

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