Device Free Localization with Capacitive Sensing Floor

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Abstract— **Passive indoor positioning has many applications including intrusion detection, fall detection of the elderly, and occupancy sensing to name a few. However, current Device Free Localization (DFL) solutions fall short of the desired accuracy requirements and are difficult to implement in a real-world scenario. This research investigates the use of a capacitive floor-based sensing solution, which can simultaneously detect multiple footsteps of a subject. The developed sensing floor prototype achieved a median positioning error of 13.5 mm and a median angular accuracy of 10.4°.**

Keywords— **Indoor localization, Device Free Localization (DFL), Capacitive Flooring, Footprint Detection**

I. Introduction

In an increasingly technologically connected world, passive indoor localization service is still a problem to be solved. Image processing or computer vision-based techniques can accurately localize and identify an un-tagged target with reasonable accuracy [1]. However, privacy is a significant concern and thus has limited utility in many applications. Whilst people may be accepting of cameras in public spaces, most people would find cameras inside their house invasive to their privacy. Many accidents, especially amongst the elderly, happen in areas where cameras would not be welcome such as in bathrooms and bedrooms. Passive localization using wireless technology has seen extensive research effort in the recent years. Wireless-based localization has the advantage of potentially being able to localize using existing infrastructure by leveraging the ubiquitous presence of wireless networks within the built environment. A survey of wireless Device Free Location (DFL) indicates a saturated research field [2]. In addition, there are some inherent disadvantages with RF wireless technology such as the limited accuracy due to multipath reflections. A more recent development has been the use of the Channel State Information (CSI) metric which uses all of the many Wi-Fi subcarriers for much improved accuracy [3]. However, commercial hardware has yet to widely support the use of this metric limiting it use to experimental setups. Passive VLP [4] works around the principle that as subjects move around a room, they cast shadows which can be detected by a light sensitive device. These shadows can then be used to estimate the subject's position. However, the passive VLP techniques are often vulnerable to change in ambient light level.

When inside a building, humans spend much of their time in contact with the floor. The major exceptions being when one is in bed, sitting with one's feet off the ground or in the bath. This therefore lends the floor a new potential purpose; namely, becoming a large sensor for both positioning and identifying people indoors. There are several works that have attempted to do this with varying degrees of success.

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There have been several works that have investigated the use of pressure sensitive floors for locating and identifying people [5, 6, 7]. Pressure sensitive floors have the advantage that they are able to sense the force at which a subject's foot hits the ground, however this is offset by the generally worse spatial resolution they offer. As such pressure sensitive floors are very good for identifying people, however they appear to be complex and expensive to build and cannot handle multiple occupants in close proximity. Capacitive sensing has mainly been used for positioning and fall detection as it is much harder to utilize it for user identification. However, it has the advantage of being easier to extend for use with multiple occupants, which is an area most pressure sensitive solutions have been unable to solve.

One of the earliest capacitive systems is Smart Carpet [8], which uses fabric into which conductive wires are sewn in serpentine patterns to form 150 mm by 150 mm panels. The system is used to estimate subject's paths through a room. Similarly SensFloor [9, 10] uses conductive triangles embedded into a textile. It was able to identify individuals when used in conjunction with a hip mounted accelerometer [11]. The authors were also able to track multiple subjects, however the details are sparse. SensFloor has since been made into a commercial product [12] and more details are not available in the published literature. Rimminen et al. [13] were similarly able to track occupants in a room using metal squares of 0.3 m by 0.3 m embedded in the floor, however the authors did not investigate the localization accuracy. The authors also demonstrated that the pattern seen from the floor is different when a person is lying on it versus standing on it, however, the authors did not provide any quantitative figures. This work was significantly improved upon in [14] where the authors used a room of 4 m by 4.5 m with sensor panels of size 0.25 m by 0.5 m. The authors tested the capacitive floor on moving subjects and found that a mean positioning error of 210 mm could be achieved. Multiple target tracking was employed using Rao-Blackwellized Monte Carlo Data Association. Two subjects could be individually separated with 90% accuracy if they were more than 0.8 m apart and with 99% accuracy if they were more than 1.1 m apart. The authors also implemented fall detection in [15] which used the previous works for tracking people and then classified poses based upon their area amongst other metrics. However, the methodology is very brief and there is very limited discussion of the results. Arshad et al. describe a similar system with a very basic proof of concept showing that a change in capacitance can be detected at a metallic electrode by a microcontroller [16]. The authors discuss how this could be used for fall detection with some very limited proof of concept testing [17]. CapFloor [18] uses two sets of parallel wires orthogonal to each other. A person walking above these changes the measured capacitance in any wires that they are above. As there are two sets of wires in orthogonal directions, a person will be above at least one wire in each direction, with the intersection point of these wires being the person's

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estimated position. The position error is given as "in the range of 50cm".

All the previously mentioned works have used loading mode [19] capacitive sensing. TileTrack [20] instead uses transmit mode where an additional electrode is placed in the room as a receiver. A square wave is transmitted from the floor tiles and received by the said electrode. The change in amplitude that is caused in this square wave by a person between the electrode and the floor tile can be detected. The squares are 0.6 m by 0.6 m and a frequency of 32 KHz used for the square wave. The system can position a stationary person to within 143 mm worst case and within 100 mm in 80% of cases. Several paths were tested, and the maximum error was found to be 407 mm. This work was further extended in [21]. A whole apartment of 69 m^2 had the floor fitted with either 0.3 m by 0.3 m squares or 0.6 m by 0.6 m squares depending on the room. The position accuracy was found to be 70 mm when standing on the on 0.3 m squares and 110 mm when standing on the 0.6 m tiles. For walking the accuracy was found to be 170 mm on the 0.3 m squares and 330 mm on the 0.6 m tiles. These accuracy values are with 90% confidence i.e. the accuracy of the 90th percentile of the data.

II. System Development

A. Key Concept

There are three main sensing modes for capacitive electric field sensing as discovered by Zimmerman et al. [22] and Smith et al. [19]: transmit mode, shunt mode and loading mode. In transmit mode the signal from the transmitter is coupled by the subject's body, which then becomes an electric field emitter. This only occurs when the subject is very close to the transmitter and the body effectively becomes an extension of the transmitter. In shunt mode, the subject's body conducts a portion of the signal to ground. The remainder of the signal which is not blocked by the subject can then be measured at the receiver. This happens when the subject is not close to either electrode. In loading mode, there is no receiver and the environment effectively forms the second plate of the capacitor to ground (Fig. 1).

A parallel plate capacitor can be modelled using the following equation:

$$C = \frac{\varepsilon_0 \varepsilon_r A}{d} \tag{1}$$

Where C is the total capacitance, ε_0 is the electric constant (8.854×10^{-12} Fm^{-1}), ε_r is the relative permittivity of the dielectric (which is assumed to be constant), A is the overlapping area of the two plates, and d is the separation between the two plates. In the case of a flooring solution, a subject stands with their foot above the transmitting plate. The capacitance then depends on two main factors – the proportion of the plate covered by the subject's foot (A) and the distance between the subject's foot and the plate (d). The distance will remain fairly constant between footsteps and between users with the main factor being their footwear. Whereas the area will change very often as sensors are usually only partially covered.

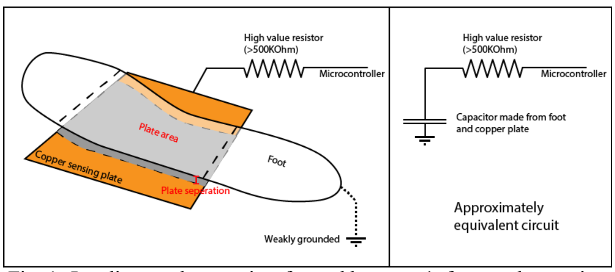

Fig. 1: Loading mode capacitor formed by a user's foot on the sensing floor

B. Hardware Design

Squares of copper are affixed to the underside of a sheet of 6 mm MDF sheet which may be seen in Fig. 2. The copper squares are 90 mm by 90 mm in size and are spaced 10 mm apart. The current testbed hardware is made up of four 0.6 m by 0.6 m panels adjacent to each other, with each panel having 36 individual copper squares (Fig. 3). Each copper square is soldered to a wire which is connected along with 35 other wires to a microcontroller where the capacitance is measured. The wires are routed along the gaps between the copper squares.

There are several ways to measure the capacitance. One can use a low frequency signal into the plate using a 30 – 100 KHz sine wave, as suggested by Smith et al. [19]. One can then measure the current of this signal using either a transimpedance amplifier or, more simply, a shunt resistor. Another method is to use the RC time constant of a capacitive circuit.

The time taken to charge a capacitor to a set voltage V_0 is given by the well-known RC charging equation:

$$V(t) = V_0(1 - e^{-t/\tau}) \tag{2}$$

Here τ is the RC time constant given by multiplying the circuit resistance by the circuit capacitance. If a high value resistance is used, the resistance can be assumed to be reasonably constant and independent of the unknown resistance to ground. The time taken for the capacitor to charge to a set value will therefore depend solely on the capacitance.

This information can be used to measure the capacitance with a microcontroller. A microcontroller's digital logic pins are set so that they have a threshold for the voltage that constitutes a digital zero and a digital one. Two digital pins are connected by a high value resistor (in the range of 1-5 M ohm). The pins shall be called the sender (S pin) and receiver (R pin). The resistor connects the two and the copper plate is attached

Fig. 2: Copper floor sensing tiles. Each tile is connected to a microcontroller with a wire.

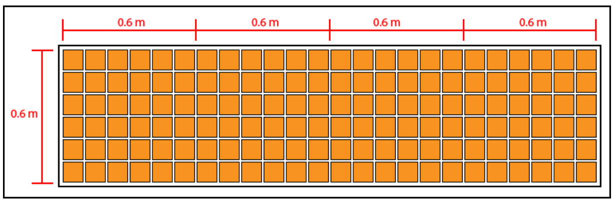

Fig. 3: Testbed copper plate layout

to the R pin. The S pin is used as an output in push-pull configuration whilst the R pin is used as an input. The S pin is set to output a logic low (GND) and a certain amount of time is waited so that the R pin has time to settle. A timer is started, and the S pin is set to output a logic high (3.3 v). The timer is stopped as soon as the R pin registers a digital 1 read. This process is repeated multiple times to reduce the measurement noise through averaging. When a subject is near the copper plate the effective capacitance is much greater than when there is no subject nearby. This leads to the pin having a much longer rise time when there is a subject in close proximity.

The circuit board is equipped with a 100 pin ARM Cortex M3 from ST Microelectronics [23]. The majority of the aforementioned pins are used for the capacitance measurements. An ESP8266 Wi-Fi module [24] is used for communications. The circuit board is shown in Fig. 4 and a block diagram of the entire system is shown in Fig. 5. The PC app is written primarily in JavaScript (nodeJS) using the electron wrapper to package it as a GUI desktop app. It hosts an http server which the devices POST data to. The IP of the server is currently hardcoded into the firmware of the ESP8266, however a small wireless router is used to create a subnet onto which all the devices and the PC running the app are connected. The IP address of the PC can then be configured through the router's DHCP server. The app has several main functions. The first is that it displays a live real time feed directly from the floor with the option to display the output of the foot detection algorithms overlaid on top. One can also use the app to configure parameters for the algorithm in real time. It also allows for recording of incoming data to a file for replaying and later analysis.

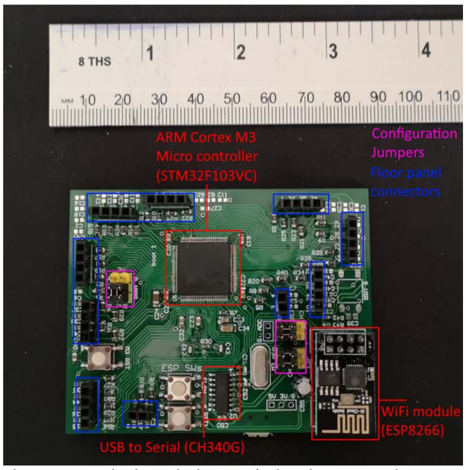

Fig. 4: The custom designed electronic hardware used to measure the capacitance of the sensing floor tiles.

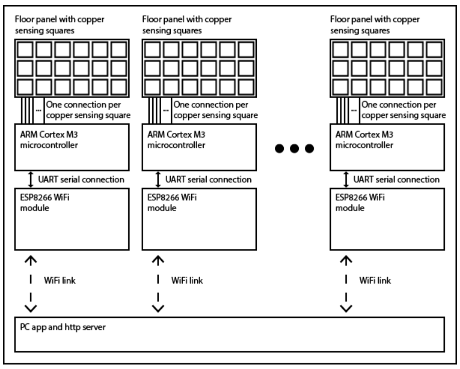

Fig. 5: Block diagram of the sensing floor

When the system is first powered on, a number (currently set to 10 after limited empirical testing) of capacitance readings are taken from the floor. These readings are then used as initial baseline readings which are then subtracted from each subsequent capacitance measurement from the floor. Over time these baseline readings tend to drift, so to counteract this several measures can be taken. Firstly, one can manually recalibrate the system by taking a new set of baseline capacitance readings periodically when the system is known to be empty. A more automated method is to take a long-term average of all capacitance readings taken whilst the system is in use and use this long-term average as the baseline. The assumption being that over a long period of time the amount of time in which a subject is standing on a square is small compared to that in which a subject is not standing on a square. However, this does mean that if a person stands still for a very long period of time they will eventually be lost by the system.

C. Foot Detection

Foot detection is done using the following algorithm. Firstly, the capacitance values from the floor are interpolated to improve the resolution. Several interpolations have been tried, with cubic interpolation performing the best. A threshold is then applied to the data, such that any capacitance values below the threshold value are set to zero and any capacitance values above the threshold value set to one. Once this has occurred, cluster detection is applied whereby all connected squares are considered to be a cluster. In the future, a more sophisticated clustering method can be used. Each cluster, representing a single footprint, can then be represented by a 2 x N matrix, M where N is the number of data points in the cluster. Each column of the matrix is a vector representing the position of a single data point in the cluster. Figure 6 shows this process. The centre of the footprint $(\bar{x}, \bar{y})$ is currently taken by averaging the position of each point in the 2 x N cluster matrix M as follows:

$$\bar{x} = \frac{\sum_{i=1}^{N} M_{1,i}}{N} \qquad \bar{y} = \frac{\sum_{i=1}^{N} M_{2,i}}{N} \tag{3}$$

The orientation of the footprint is then found by using Principal Component Analysis (PCA) [25]. The covariance of two vectors can be calculated as follows:

$$cov(a, b) = \frac{\sum_{i=1}^{N} (a_i - \bar{a})(b_i - \bar{b})}{N} \tag{4}$$

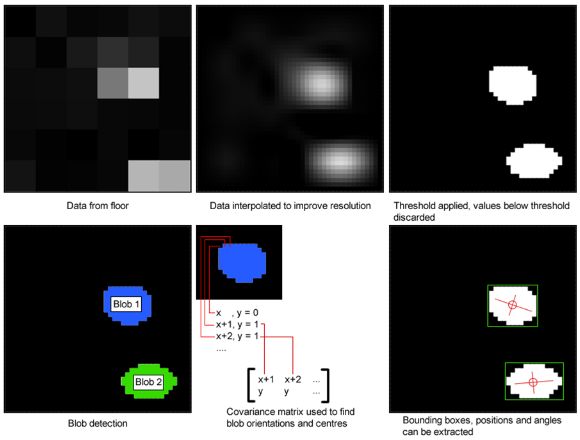

Fig. 6: Foot detection process

A covariance matrix M_{cov} can be formed by taking the top row of M to be the vector, a and the bottom row the vector, b. The vector a is a vector containing all the x positions of each point in the cluster and the vector b is a vector containing all the y positions of each point in the cluster.

$$M_{cov} = \begin{bmatrix} cov(a,a) & cov(a,b) \\ cov(b,a) & cov(b,b) \end{bmatrix} \tag{5}$$

The eigenvectors of this matrix can then be used to calculate the vectors of the orientation of the foot. The bounding box of the foot can be found by taking the maximum and minimum x and y positions of the points in the cluster.

III. System Performance

A. Position Accuracy

To investigate the position accuracy of a subject's footprint on the floor, fifteen locations were chosen. The position of the subject's foot was measured using a ruler and measurements were taken from the floor itself. The ruler was used as the ground truth to verify the position estimates from the sensing floor against. The outline of the subject's right foot was drawn onto a sheet of cardboard and cut out. A square corner was left protruding from the top left to measure against. The distance was measured from both the top and right edges of the sensing floor to this protruding corner of the footprint. This is shown in Fig. 7. An attempt was made to keep the foot's orientation constant between measurements but was only done by visual estimation and therefore, the orientation varied by approximately ±5° between measurements.

After performing the test at the15 locations on the sensing floor, the median position error was found to be 13.5 mm and the maximum position error was found to be 25.6 mm. Figure 8 shows the positions of each location and the error at each location.

It should be noted that the ground truth was measured to the top right corner of the foot outline, whereas the floor is estimating the position of the centre of the foot. Therefore, a variation in the orientation of the foot causes the error to increase due to the offset. Hence the measured errors are likely to be in part due to the methodology and it is believed that the error could potentially be lower, with a more accurate ground truth. Also, the ground truth and estimated values are at different positions on the foot, the estimated results must be translated so that they match up. This translation is applied uniformly to all the estimated results. However, the calculation of the translation assumes that the errors are evenly distributed in all directions and therefore the translation is taken to be the median of the error on each axis.

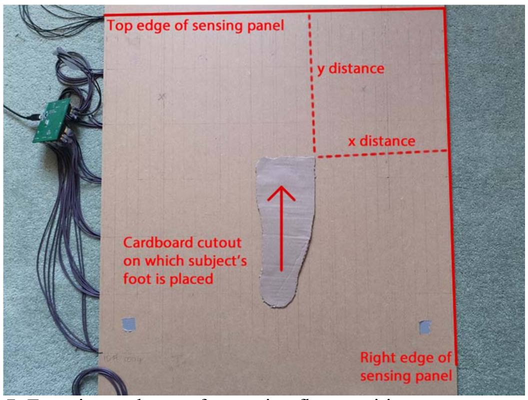

Fig. 7: Experimental setup for sensing floor position accuracy testing.

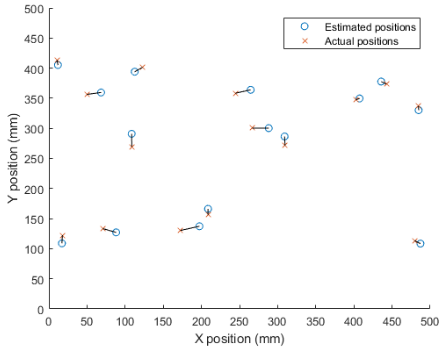

Fig. 8: Estimated vs actual positions of a test subject's foot on the sensing floor

B. Angular Accuracy

A test was undertaken to investigate the accuracy of estimating the subject's foot angle. A similar setup was used to that in the position accuracy testing. Using a protractor, lines were marked out at 10-degree increments from 0° to 90° and an extra line at 45°. The same cardboard cut-out was used to locate the foot with minor modifications. A slit was added down the centre of the foot cut out so that the lines can be seen underneath as well as the origin point about which the rotation was done. Capacitance samples were taken over a period of 5 seconds at each angle and from this the foot angle is estimated. The setup can be seen in Fig. 9.

The median angular error was found to be 10.4° and the maximum angular error was found to be 18.8°. Figure 10 shows the error for different angular orientations of the subject's foot. The error shows strong signs of non-linearity which means it may be possible to correct for this in the detection algorithm. Further investigation is required as this may depend on the location of the foot with respect to the copper squares underneath the floor. Therefore, this same test needs to be performed at different locations on the floor. Improving the accuracy is desirable as the foot angle is a possible metric to be investigated for gait identification.

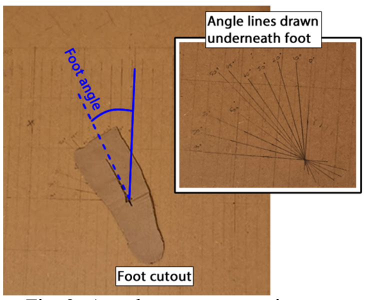

Fig. 9: Angular accuracy testing setup

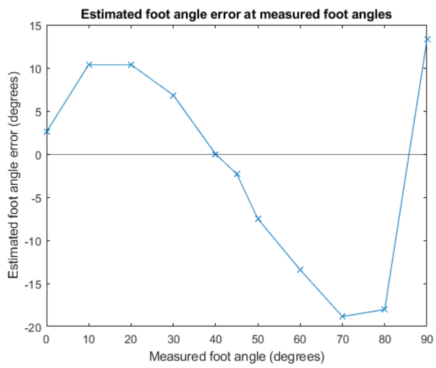

Fig. 10: Estimated foot angle error with respect to actual foot angle.

C. Foot Detection

Currently, whilst detection of multiple feet has been implemented, no quantifiable data on the performance has been collected. The system has been tested with multiple subjects and can detect the feet of several subjects concurrently given that they are sufficiently spaced apart. Figure 11 shows both of a subject's feet being detected individually. The position of each foot is marked by the intersection of the red lines, with the longer line corresponding to the orientation. The orientation is only valid in a 180-degree hemisphere. This means that assumptions must be made about the direction the foot is facing. One can assume that people generally walk forwards rather than backwards, so over the course of several footsteps, one can deduce the direction of the foot. It has been observed that feet on adjacent squares can get lost as they merge with each other into a larger blob. As the copper sensing squares are 100 mm wide, providing the feet are greater than around 150 mm apart, they do not appear to alias. This is because the partial occlusion of feet at the very edge of adjacent squares does not put them over the threshold.

IV. Conclusion and Future Works

The developed capacitive floor can position a subject's foot with a median position error of 13.5 mm and a median angular error of 10.4°. It has the potential to be an accurate, yet noninvasive passive localization system. The current solution is still in early stages of development with scope for future improvements. Whilst multiple footprints can be simultaneously located, estimation of a subject's body position from a set of successive footprints has not been implemented. Further work is needed to identify an individual from their gait pattern and develop a classification model to detect poses of people lying on the floor. This could then be used to monitor for falls and if necessary, alert caregivers or emergency services to such an event.

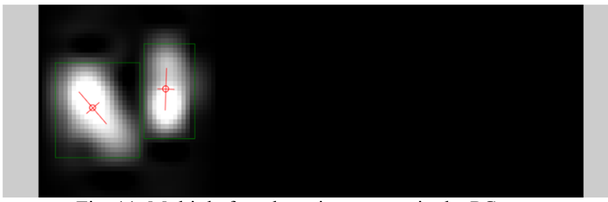

Fig. 11: Multiple foot detection as seen in the PC app.

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