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CapLoc: Capacitive Sensing Floor for Device-Free Localization and Fall Detection

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ABSTRACT Passive indoor positioning, also known as *Device-Free Localization* (DFL), has applications such as occupancy sensing, human-computer interaction, fall detection, and many other location-based services in smart buildings. Vision-, infrared-, wireless-based DFL solutions have been widely explored in recent years. They are characterized by respective strengths and weaknesses in terms of the desired accuracy, feasibility in various real-world scenarios, etc. Passive positioning by tracking the footsteps on the floor has been put forward as one of the promising options. This article introduces CapLoc, a floor-based DFL solution that can localize a subject in real-time using capacitive sensing. Experimental results with three individuals walking 39 paths on the CapLoc show that it can detect and localize a single target's footsteps accurately with a median localization error of 0.026 m. The potential for fall detection is also shown with the outlines of various poses of the subject lying upon the floor.

INDEX TERMS Capacitive Sensing, Device-Free Localization, Electric Field Sensing, Fall Detection, Footstep Detection, Footstep Tracking, Human Sensing, Indoor localization, Indoor Positioning System (IPS), Passive Positioning.

I. INTRODUCTION

Passive indoor positioning is the key enabling technology for applications like *Ambient Assisted Living* (AAL) and *Human-Computer Interaction* (HCI). Unfortunately, even with the attention of researchers for over two decades, passive positioning or *Device-Free Localization* (DFL) remains a problem to be solved. Camera-based techniques can accurately locate and identify a tag-less target with reasonable accuracy [1]. However, they require good lighting conditions and are adversely impacted by occlusion. More importantly, privacy is a significant concern making such systems less acceptable in many applications, especially in a residential setting. Many accidents and falls happen in places such as bathrooms and bedrooms where cameras would be considered to be invasive. While efforts are underway to utilize privacy-preserving single-pixel cameras [2, 3], it is still early days for such a technique.

Passive localization using *Radio Frequency* (RF) sensing has been extensively researched in recent years [4, 5]. While RF-based localization has the advantage of potentially being able to repurpose the wireless networks within the built environment, there are some inherent disadvantages like limited accuracy due to multipath reflections. Application of the *Channel State Information* (CSI) metric utilizing many Wi-Fi subcarriers can mitigate the multipath issue [6] to achieve much-improved accuracy [7-9] and even perform sophisticated tasks like activity recognition [10]. However, CSI is not available for the majority of the RF technologies (e.g., Bluetooth and ZigBee). In addition to this, most consumer-grade Wi-Fi hardware is yet to widely support the use of this metric thus limiting its practicality.

Passive *Visible Light Positioning* (VLP) [11, 12] is based on the principle that the presence of a subject alters optical channels. These changes can be detected by nearby light-sensors as variation in the *Received Signal Strength* (RSS) of the light level and subsequently used to estimate the subject's position. However, the majority of passive VLP techniques are vulnerable to change in ambient light levels. Also, they need good illumination conditions. *Infrared* (IR) sensing has been proposed as an alternative way for DFL by detecting the heat signature of a human target. *Passive IR* (PIR) sensors, commonly available as motion detectors, have been used for such localization [13-16]. However, PIR sensors require

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TABLE 1. Comparison of CapLoc with other floor-based positioning systems.

Research	Sensing Method	Position Accuracy
Liau et al. [19]	Pressure	85-percentile error of 0.283 m
Andries et al. [20]	Pressure	Mean error of 0.13 m for a single person, 0.2 m for two people
Al-Naimi et al. [21]	Pressure	Mean error 0.0767 m
Murakita et al. [22]	Binary Pressure Sensors	Mean error of 0.2 m
Mirshekari et al. [23]	Vibration	Median localization error of 0.38 m
Alajlouni et al. [24]	Vibration	80-percentile error of 0.7 m
Poston et al. [25]	Vibration	RMSE of 0.6 m and 0.8 m in two separate environments
Smartcarpet [26]	Capacitive	MSE 0.0187 m (line) to 0.431 m (C-shape) for various trajectories
Rimmeinen et al. [30, 31]	Capacitive	Mean position error of 0.21 m
Capfloor [32]	Capacitive	"In the range of 50 cm"
Tiletrack [34, 35]	Capacitive	80-percentile error 0.1 m
CapLoc (This paper)	Capacitive	Median error 0.026 m, 90-percentile error 0.066 m

TABLE 2. Comparison of CapLoc with other passive positioning systems.

Research	Sensing Method	Position Accuracy
Watchers on the Wall [11]	Passive VLP	Median error 0.12 m
FieldLight [12]	Passive VLP	Median error 0.68 m to 1.2 m
D Yang et al. [14]	PIR	Mean error 0.21 m
B Yang et al. [15]	PIR	Mean error < 0.8 m
Liu et al. [16]	PIR	Mean error 0.47 m to 0.71 m
Tang et al. [42]	Passive EFS	Mean error 0.104 m to 0.272 m
P-Loc [43]	Passive EFS	Mean error 0.48 m
Zhao et al. [3]	Single pixel camera	Mean error 0.2 m
Tariq et al. [37]	Capacitive wall sensors	Mean error 0.307 m
Chen et al. [18]	Thermophile	RMSE of 0.19 m
Qu et al. [17]	Thermophile	Mean error 0.07 m
Zhang et al. [8]	Wireless CSI	Mean error 0.8 m
Shi et al. [9]	Wireless CSI	Mean error 0.63 m
SpringLoc [5]	Wireless RSSI	Median error 0.6 m to 1.57 m
CapLoc (This paper)	Capacitive	Median error 0.026 m, 90-percentile error 0.066 m

relative motion between the sensors and a target. Therefore, they are unable to deal with a stationary target. IR-sensing based positioning using thermopile sensors has been proposed [17, 18] to deal with both stationary and mobile targets. Unfortunately, such techniques are inherently vulnerable to changes in heat signatures resulting from clothing variations.

Humans spend much of their time in contact with the floor when they are inside a building. Therefore, the floor can be potentially repurposed as a large sensor for device free positioning of individuals. Table 1 summarizes the key works in the area of the floor-based DFL.

Pressure-sensitive floors [19-21] have been used for locating and identifying people. There are also systems using binary pressure-sensitive switches built into the floor [22]. Unfortunately, the pressure-sensitive floors appear to be complex to build. Besides, the pressure sensors (e.g., load cells) are also subject to wear and tear degradation, especially of the mechanical components.

Floor-based localization can also be accomplished by measuring footsteps-induced vibrations with a network of seismic sensors [23-25]. The footsteps (and hence the target) are located by exploiting the fact that vibration signals take different times to reach each sensor depending on the distance between the footstep and the sensors. This allows performing the localization using Time of Arrival (ToA) or Time Difference of Arrival (TDoA) techniques [25]. However, the floor is a complex heterogeneous medium. It varies significantly from one building to another. This makes the calibration challenging thus complicating the transfer of a relevant system between different premises.

Capacitive sensing utilizing the change in capacitive coupling between a custom-designed floor and target can be an effective localization method. In this scenario, the floor and the target form (two plates of) a capacitor. The presence of the target alters the electric field, actively generated by a transmitter, manifesting as a measurable change in the capacitance. Smart Carpet [26] uses fabric into which conductive wires are sewn in serpentine patterns to form 0.15 m × 0.15 m panels. Similarly, SensFloor [27-29] uses conductive triangles embedded into a textile. Capacitive floor with metal squares was utilized in [30, 31]. CapFloor [32] uses two sets of parallel wires orthogonal to each other. A person walking above them changes the measured capacitance in these wires. Since a person is above at least one wire in each direction, an intersection point of these wires presents the person's estimated position.

In contrast to the aforementioned works that use the loading mode of the capacitive sensing [33], TileTrack [34, 35] employs the transmit mode. A square wave signal transmitted from the floor tiles is received by an additional electrode placed in the room as a receiver. The detected change in the signal amplitude caused by a person between the electrode and the floor tile helps infer the location. Capacitive sensing is also utilized in research [36, 37] where instead of using the floor-based solution, electrodes are set up on the walls.

When a person walks on a typical floor, a charge is built up due to the *Triboelectric Effect* [38]. The person can also be

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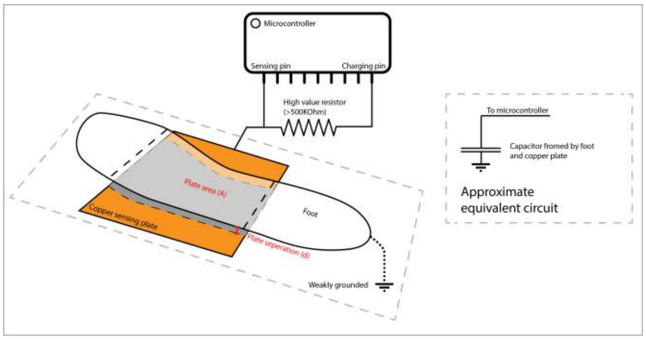

FIGURE 1. **Loading mode capacitor formed by subject's foot on CapLoc, along with a simplified circuit diagram. *A* is the overlapping area of the two plates, and *d* is the separation between the two plates.**

FIGURE 2. **The structure of the floor. The floor can be topped with any non-conductive flooring material such as wood, vinyl or carpet.**

considered as being an earthed conductor. Therefore, the ambient electric field created by the radiation from the AC powerlines (ever-present in buildings) is altered by the presence of a human target. This change can be measured with *Electric Potential Sensors* (EPS) and used for both identification of subjects [39] as well positioning of them [40-43]. Unfortunately, such opportunistic, passive electric sensing is vulnerable to ambient electrical field noise and interference. The relevant systems are mainly implemented using EPS units that are placed on the walls or ceiling of a room.

This paper proposes a new capacitive floor system named CapLoc for passive positioning. In a preliminary work [44], the authors presented how a static foot can be detected when a subject stands barefoot on a capacitive sensing panel. This paper utilizes that concept to develop CapLoc, a positioning system, for real time localization of a moving target accurately and potentially detect fall in an automated manner. It presents the following original contributions:

1. CapLoc can determine the position of a mobile target in real-time. It is not data-driven and therefore, requires minimal calibration for localization making it more invariant to changes in the setting. CapLoc is also robust and not vulnerable to factors that adversely affects other DFL systems like wireless multipath propagation (affects wireless DFL), illumination condition (impacts camera and passive VLP systems), clothing worn by the target (affects IR-based systems) etc.;
2. The experimental results showing the localization of a mobile target for multiple trajectories are presented. The median and 90 percentile localization errors while testing with three different subjects are found to be 0.026 m and 0.066 m, respectively. This makes CapLoc more accurate than most passive localization systems reported in the literature (see Tables 1 & 2). Also, the majority of the reported DFL systems were only tested for a handful of target trajectories. In contrast, CapLoc was tested for 39 different paths walked by multiple subjects. An accurate ground truth recording system was implemented using virtual reality technology (HTC Vive [45]) to ensure that the localization error is accurately measured. By utilizing the procedure outlined in the article, other researchers will be able to record accurate ground truth in an automated manner, using an affordable consumer grade technology;
3. It is shown that the poses of a person lying on the floor can be captured easily. Potentially, this can be used for automated fall detection in a non-obtrusive manner.

The rest of the paper is organized as follows. Section II discusses the development of the CapLoc system. Section III presents the footstep detection process. Section IV demonstrates the localization performance. Pose capture for potential fall detection is shown in Section V. Section VI concludes the paper and discusses future research directions.

II. SYSTEM DEVELOPMENT

A. KEY CONCEPT

CapLoc is based on the formation and the subsequent sensing of loading mode capacitance [33, 46]. The concept is shown in Fig. 1 where the subject's foot and copper-foil tiles underneath the floor form the two plates of the capacitor. This capacitor can be modeled as:

$$C = \varepsilon \frac{A}{d} , \tag{1}$$

where C is the total capacitance, ε is the permittivity of the dielectric (assumed to be constant), A is the overlapping area of the two plates, and d is the separation between the two plates (details shown in Fig. 1). When the subject stands with a foot above the transmitting plate, the capacitance 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). For a rigid floor type, the distance d remains fairly constant, whereas the area A changes as sensors could naturally be covered to a different extent.

B. PROTOTYPE HARDWARE DESIGN

A 0.6 m × 0.6 m sensing panel, with 25 individual copper-foil squares, is the basic building block of the CapLoc floor (Fig. 2 and 3). Each copper square is soldered to a wire that is connected along with 24 other wires to a microcontroller (100-pin ARM Cortex M3 [47]) where the capacitance is measured. The wires are routed within the gaps between the copper squares. The total component cost of a 0.6 m × 0.6 m sensing panel (excluding the cost of floorboards) is approximately $6.

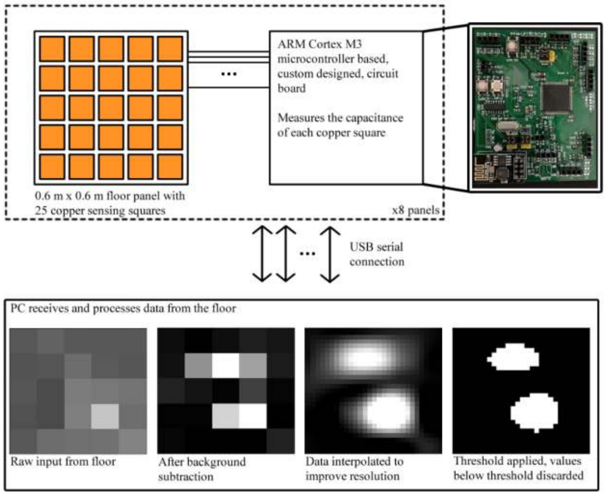

FIGURE 3. **Block diagram of the CapFloor system architecture, with the custom designed hardware sampling the capacitance values which are sent to the PC app for the foot detection process. The foot detection is performed by adopting image processing techniques.**

Therefore, the cost of implementing CapLoc, excluding labour, is less than \$18/sqm while offering significant functionality. Also, the cost of the system is expected to decrease significantly with mass manufacture.

The capacitance is measured by evaluating the RC time constant of the equivalent capacitive circuit. The time taken to charge a capacitor to a set voltage V_0 is given by the well-known RC charging equation:

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

where $\tau = RC$.

If the selected resistance value R is sufficiently high, it can be assumed to be reasonably constant and independent of the unknown resistance to the ground. Time taken by the capacitor to charge to a set value, therefore, depends solely on the capacitance. A microcontroller is used to charge the copper plate through a high value resistor by applying a voltage to the charging pin (Fig. 1). The time taken to reach a set voltage at the sensing pin is measured. When a subject's foot is near the copper plate, the effective capacitance is much greater than when there is no subject nearby. This leads to a significantly longer rise time of the signal. The raw capacitance measurements are sent from the microcontroller to an application running on PC over the USB serial communication line. The PC app processes and displays the incoming data in real-time as well as saves the data for further analysis. The footstep detection algorithm takes less than 2 ms to run on a standard desktop PC running at 3.2 GHz. Trace drawing on the screen takes around 15-20 ms. The floor is sampled at around 10 Hz, giving the app plenty of time to process each frame whilst waiting for the next data frame from the sensors.

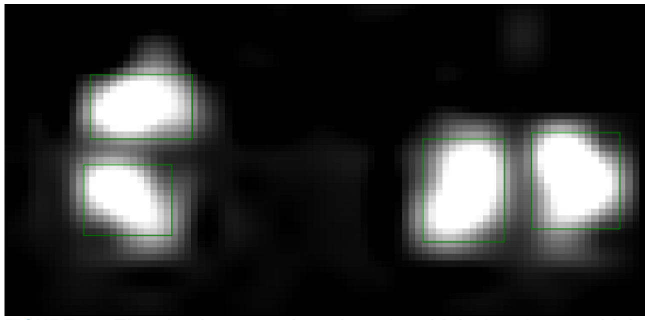

FIGURE 4. **The simultaneous detection of multiple feet from multiple subjects (interpolated, before thresholding).**

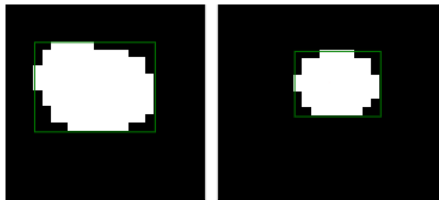

FIGURE 5. **Foot after thresholding in socks (left) and in thick soled footwear (right). In thick footwear the foot is smaller in area after thresholding.**

C. FOOT DETECTION

Figure 3 illustrates the foot detection process that is effectively an image processing algorithm where each capacitance value from the floor is represented as a single grayscale pixel. When CapLoc is first powered on, a number (currently set to 10 after many rounds of empirical testing) of capacitance readings are taken from the floor sensors as a background estimation. It is then subtracted from each subsequent capacitance measurement from the floor. Over time the background estimations can drift. To counteract this phenomenon, periodic CapLoc recalibration can be implemented by taking a new set of baseline capacitance readings when the floor is known to be vacant. Over a long period, the amount of time when a subject is standing on a

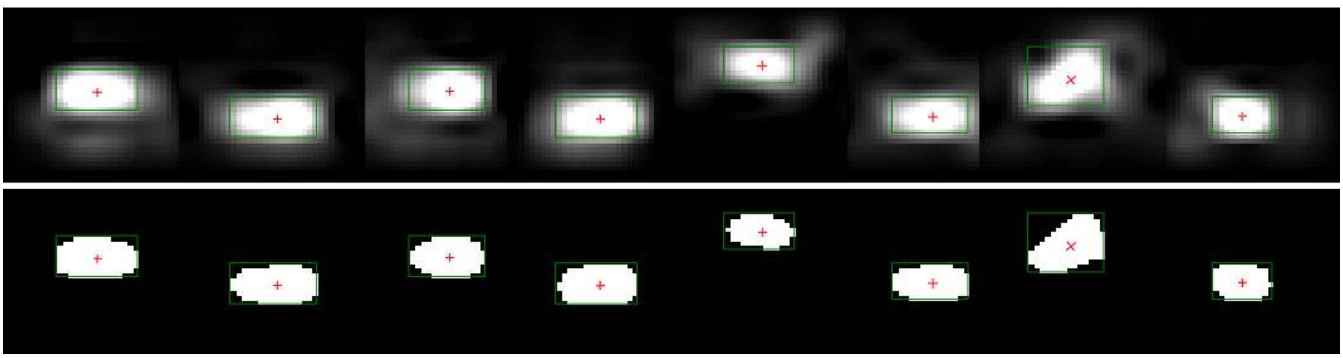

FIGURE 6. **A sequence of footprints superimposed in time. Both pre (top) and post (bottom) thresholding. Estimated center of the foot marked with a cross.**

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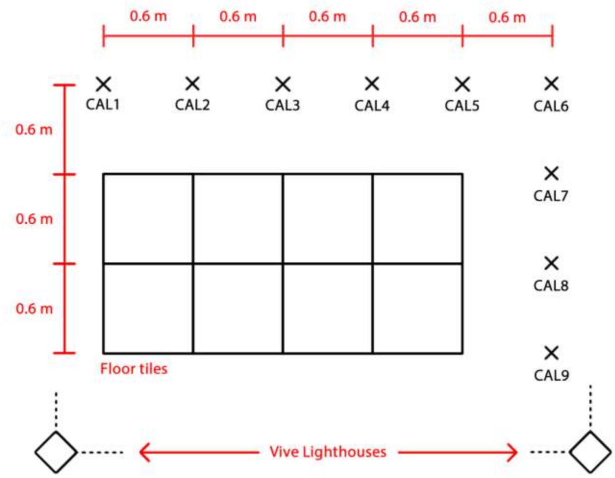
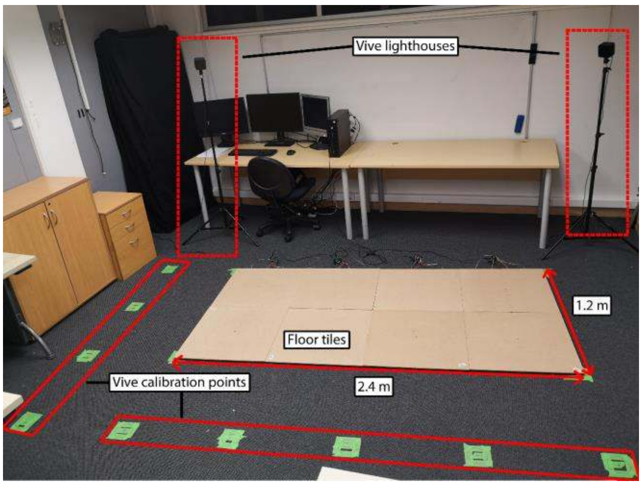


(a) **Layout diagram of experimental setup**



(b) **Photo of experimental setup**

FIGURE 7. Layout of the floor and Vive calibration points.

square is small compared to that when the subject is not standing on it. Therefore, an alternate method is to take a long-term average of all capacitance readings taken whilst the system is in use and employ this long-term average as the baseline.

In terms of image processing, the measured capacitance values form a very low-resolution image. Interpolation is applied to improve its quality. Several interpolation algorithms were tried. Cubic interpolation showed the best performance while enhancing 2 × 2 images to 7 × 7 interpolated ones.

A threshold is then applied to the data such that any capacitance values below the threshold are set to become “0” while those above the threshold are set to be “1”. Once it is done, blob detection through connected component analysis [48] is applied whereby all connected squares are considered to be a part of the blob or cluster. Each blob corresponding to a single footprint can then be represented by a matrix $\mathbf{M}$ of 2 × N dimension, 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.

The center of the footprint $(\bar{x}, \bar{y})$ is estimated by averaging the position of each point in the 2 × N cluster matrix $\mathbf{M}$ as:

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

The system was tested with multiple subjects. It detected the feet of several subjects concurrently given that they were sufficiently spaced apart. Fig. 4 shows two subjects’ feet being detected individually. It was observed that feet on adjacent squares might be non-detectable as they merged into a larger blob. The copper sensing squares are spaced at 120 mm intervals thus providing that the feet separation is to be greater than around 200 mm to avoid the aliasing. This is because the partial occlusion of feet at the very edge of adjacent squares does not put them over the threshold. Initial testing, as reported in [44], found that the position of the subject’s foot in a static situation could be measured accurately.

When the target is barefoot, the separation between the target’s foot and the copper-foil (d of Fig. 1 and Equation 1) is the smallest. This results in a larger value of the capacitance compared to the case when a subject is wearing a footwear. Therefore, CapLoc enjoys the highest SNR when the subject is barefoot which is quite common in a home setting. The impact of footwear type on foot detection accuracy was thus investigated. It was found that the type of footwear had quite a minimal effect. Figure 5 demonstrates the cases where a subject stands on the floor wearing socks and a pair sneakers with thick soles. Whilst one can see the image for the foot in the sneaker is slightly smaller (due to it being further from the sensing squares), it is still detectable with its position being relatively unaffected.

III. FOOTSTEP LOCALIZATION

A test floor was set up using eight sensing panels to create 1.2 m × 2.4 m area. Data from the system were sampled at 10 Hz making it possible to track a person moving around the floor. Firstly, individual footprints were detected, and the center of each footprint was stored. The footprint centers were then clustered in time and space to determine if they come from the same footstep. The path of the subject was then estimated by taking the midpoints of the successive footsteps. Figure 6 shows the detected footprints from a subject walking on CapLoc (in 0.6 m × 4.8 m configuration).

Implementation of an accurate ground truth system to compare the estimated path with the actual one is a challenging task. Several approaches were reported in the literature. While motion capture can provide an extremely accurate ground truth [14], it is not cost-effective. The use of the Xbox Kinect was reported in the study [40]. A custom-designed solution was reported in [31] whereby a hat on the subject’s head was connected via wires to pulleys with attached encoders.

In this work, the HTC Vive [45] was used as a ground truth system due to its low cost, availability, and sufficient

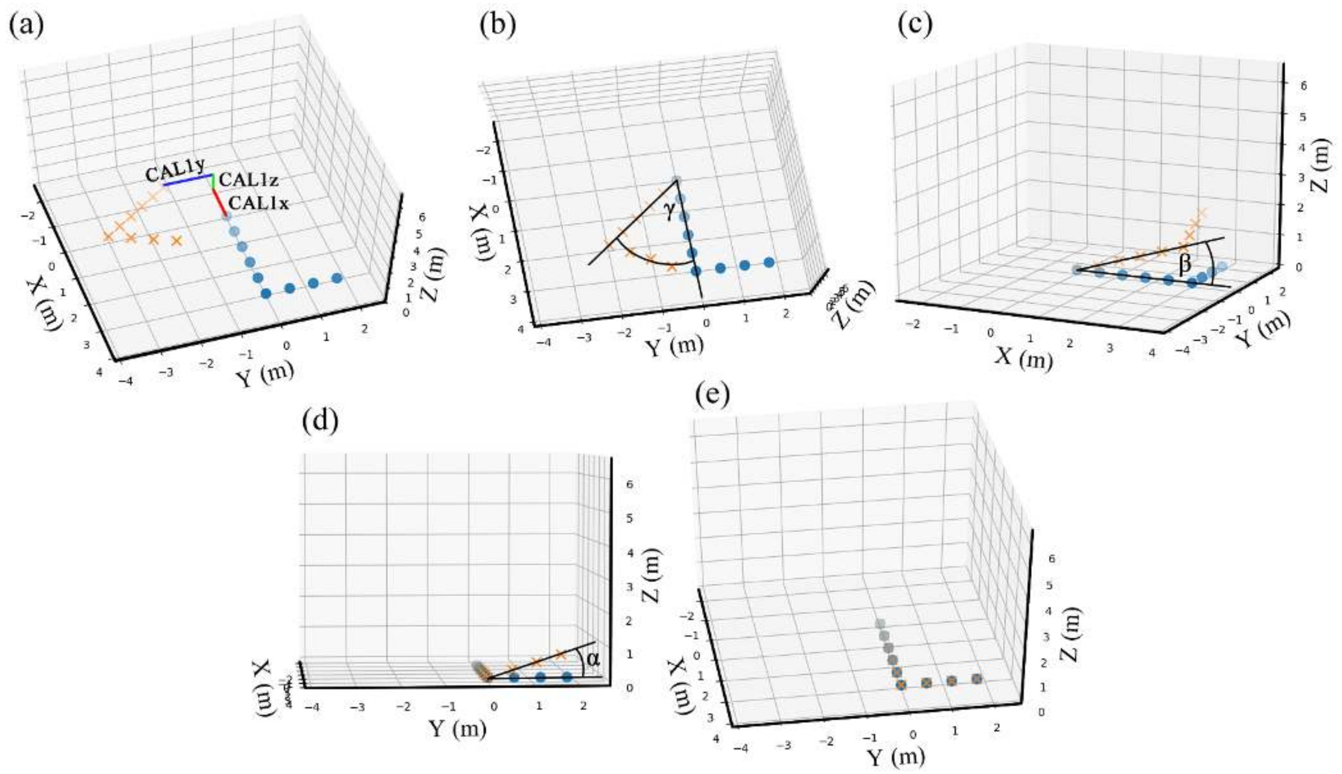


FIGURE 8. **The process of aligning the Vive's calibration points with the floor. The orange crosses represent the calibration points in the Vive's frame of reference, the blue circles in the floor's frame of reference. (a): Translating the points so that the origins are aligned. (b): Rotating about the Z axis; (c): Rotating about the Y axis; (d): rotating about the X axis; (e): the final outcome with the two sets of points aligned. Note that, the angles (especially α and β) have been exaggerated for clarity. In reality, the translation and the rotation γ were usually enough for the ICP algorithm to align the points correctly.**

FIGURE 9. **The Vive tracker affixed atop a subject's head.**

accuracy. It uses two base stations (called Lighthouses) to track a small device called Tracker.

In pre-experimental testing, the accuracy of the system was evaluated using an x-y CNC plotter with max deviation of 0.025 mm. Vive was found to be accurate within 10 mm. The positions reported by the Vive are relative to the primary lighthouse. To reconcile this coordinate system to that of the floor, a calibration process needs to be undertaken. This also means that positions of the lighthouses do not need to be carefully measured thus eliminating a potential source of error.

First, the ground truth system was calibrated using nine points around the edge of the floor (Fig. 7). The calibration points were used to align the Vive's reference plane with the floor as well as to align point CAL1 with the origin of the floor. The calibration points were used to generate a transformation matrix ($\mathbf{R}$) that was then applied to all positions measured using the Vive.

$$\boldsymbol{x}' = \mathbf{R}\boldsymbol{x}, \tag{4}$$

Where [49]

$$\mathbf{R} = \mathbf{T_v} \cdot \mathbf{R_z} \cdot \mathbf{R_y} \cdot \mathbf{R_x} \tag{5}$$

and

$$\mathbf{T_v} = \begin{bmatrix} 1 & 0 & 0 & -CAL1_x \\ 0 & 1 & 0 & -CAL1_y \\ 0 & 0 & 1 & -CAL1_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{6}$$

$$\mathbf{R_z}(\gamma) = \begin{bmatrix} \cos\gamma & -\sin\gamma & 0 & 0 \\ \sin\gamma & \cos\gamma & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{7}$$

$$\mathbf{R_y}(\beta) = \begin{bmatrix} \cos\beta & 0 & \sin\beta & 0 \\ 0 & 1 & 0 & 0 \\ -\sin\beta & 0 & \cos\beta & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{8}$$

$$\mathbf{R_x}(\alpha) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha & 0 \\ 0 & \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

Here $\boldsymbol{x}$ is a position from the Vive to be transformed, and $\boldsymbol{x}'$ is the transformed position relative to the floor. The values α, β,

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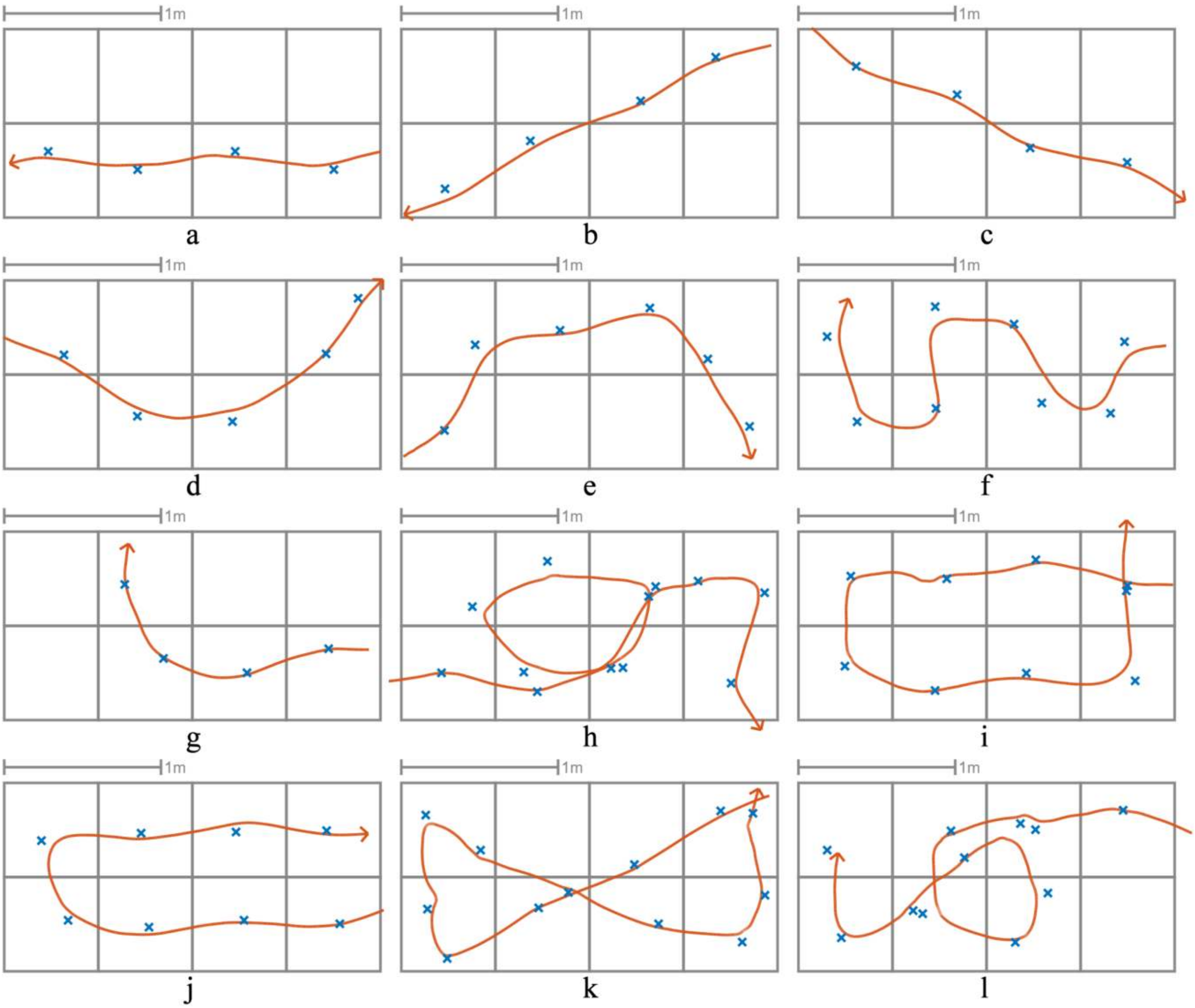

FIGURE 10. **Twelve paths walked by Subject 1 on CapLoc: crosses represent the estimated foot positions and the lines show the ground truth (Vive tracker).**

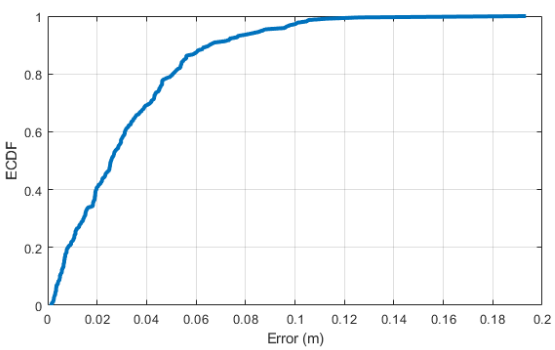

FIGURE 11. **ECDF of localization error for 219 footsteps across 39 different paths. The median error was found to be 0.026 m and the 90 percentile error 0.066 m.**

and γ are the *pitch*, *yaw,* and *roll* between the Vive's reference plane and the floor. Figure 8 illustrates the aforementioned process.

It was then further refined by employing the *Iterative Closest Point* (ICP) algorithm [50] to generate a transformation matrix aiming to minimize the Euclidean error between the measured and actual positions of all nine calibration points. The combination of the two transformations was then used to transform the position data from the Vive.

Literature reports [51-53] suggest that tracking could be lost when a line of sight is absent between the lighthouses or between the tracker and the lighthouses. The tracker was therefore attached to the top of the subject's head (Fig. 9) to maintain a constant line of sight with the two lighthouses that were mounted at approximately 2 m above the ground, one on each side of the testbed.

Thirty-nine different paths, split between three subjects - two males (subjects 1 and 2) and one female (subject 3), were walked across CapLoc with the ground truth of the subject's head being recorded by the Vive. Fig. 10 shows the footsteps estimated by CapLoc and the position of the subject's head tracked by the Vive for 12 of the total 39 paths. It can be seen that the footsteps very closely match the ground truth. Localization errors were computed by considering the position

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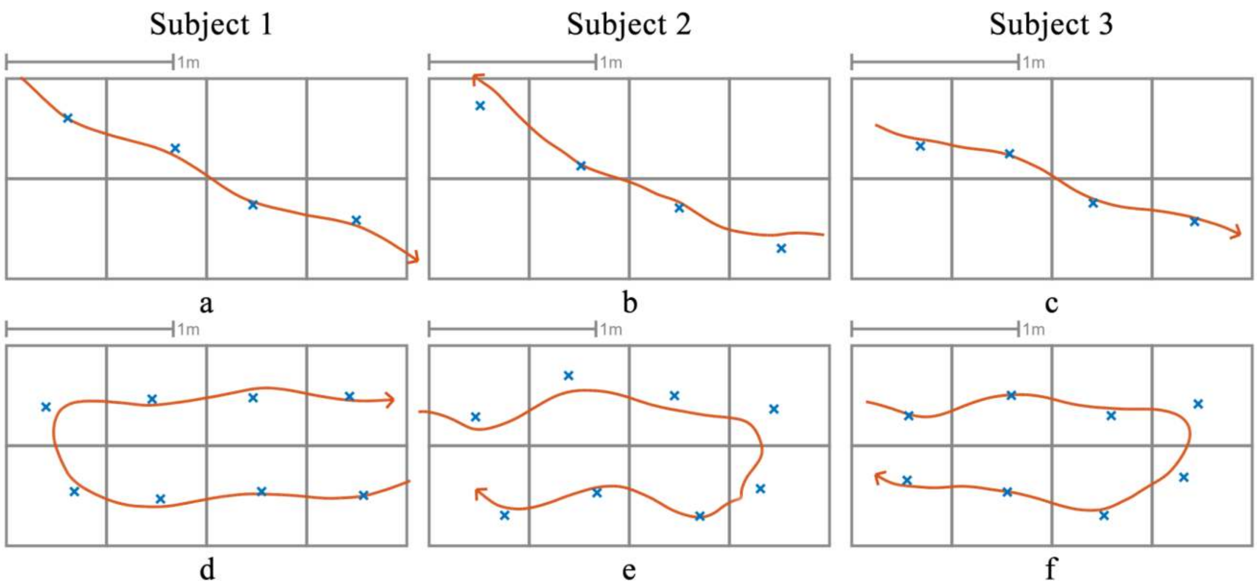

FIGURE 12. Paths walked by different subjects without the need for calibration in between.

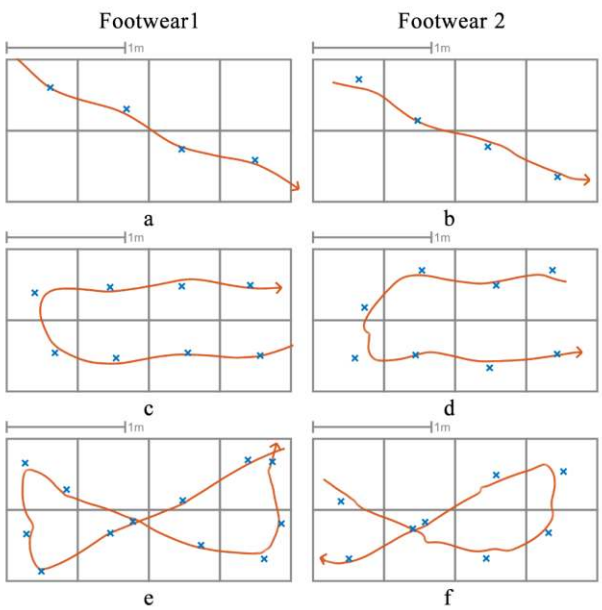

FIGURE 13. Paths walked in thin (1) and thick-soled footwear (2).

TABLE 3. Comparison of path tracking error for different subjects.

	Median (m)	90 Percentile (m)
Subject 1	0.025	0.056
Subject 2	0.039	0.097
Subject 3	0.026	0.069
Subject 1 - thick shoes	0.031	0.082

of the subject to be the midpoints between the successive footprints and then comparing them to the relevant points of the Vive's reported path. *Empirical Cumulative Distribution Function* (ECDF) for the 219 footsteps corresponding to all 39 trajectories is shown in Fig. 11.

Both U-shaped and diagonal trajectories were walked by all three subjects, due to those being easily repeatable paths. That was done to verify that the floor was able to locate different subjects without the need for calibration in between. Figure 12 shows two paths for each subject. Table 3 shows the median and 90 percentile errors for each of the subjects.

Five of the paths were walked by subject 1 in a pair of sneakers having a thick sole. Other than that, the three subjects had similar footwear, considerably thinner than the sneaker. The results are shown in Fig. 13 and Table 3. For subject 1, the median and 90 percentile errors are slightly worse for the thick-soled footwear as the measured capacitance was lower (due to higher separation from copper-foil plates, please see Section II for more details), and therefore it was more affected by noise.

The results support the assertion that the floor can be used for human tracking without any foreknowledge of the subject or environment. The only requirement being that the floor must be vacant for several seconds after the initial powering on to measure the background capacitance.

Potentially, the error could be further reduced by employing a more sophisticated path estimation algorithm. Also, accurate tracking is complicated by the impossibility to define the subject (person) as a single point object. The top of the head is approximately in the center of the subject when viewed from a top-down perspective. However, when people walk, they tend to sway from side to side. This was noticed to be even more prevalent when a subject walked along pre-marked paths. Besides, the amount of the head movements is normally somewhat higher than that of the center of mass of the body, thus causing additional errors. This can be seen in the paths and error statistics for Subject 2, which are worse than those for the other two subjects. The U-shaped path in particular shows this subjects' propensity to move their heads as they walk. The head movements resulting from the subject's walking pattern may have as much or even more effect

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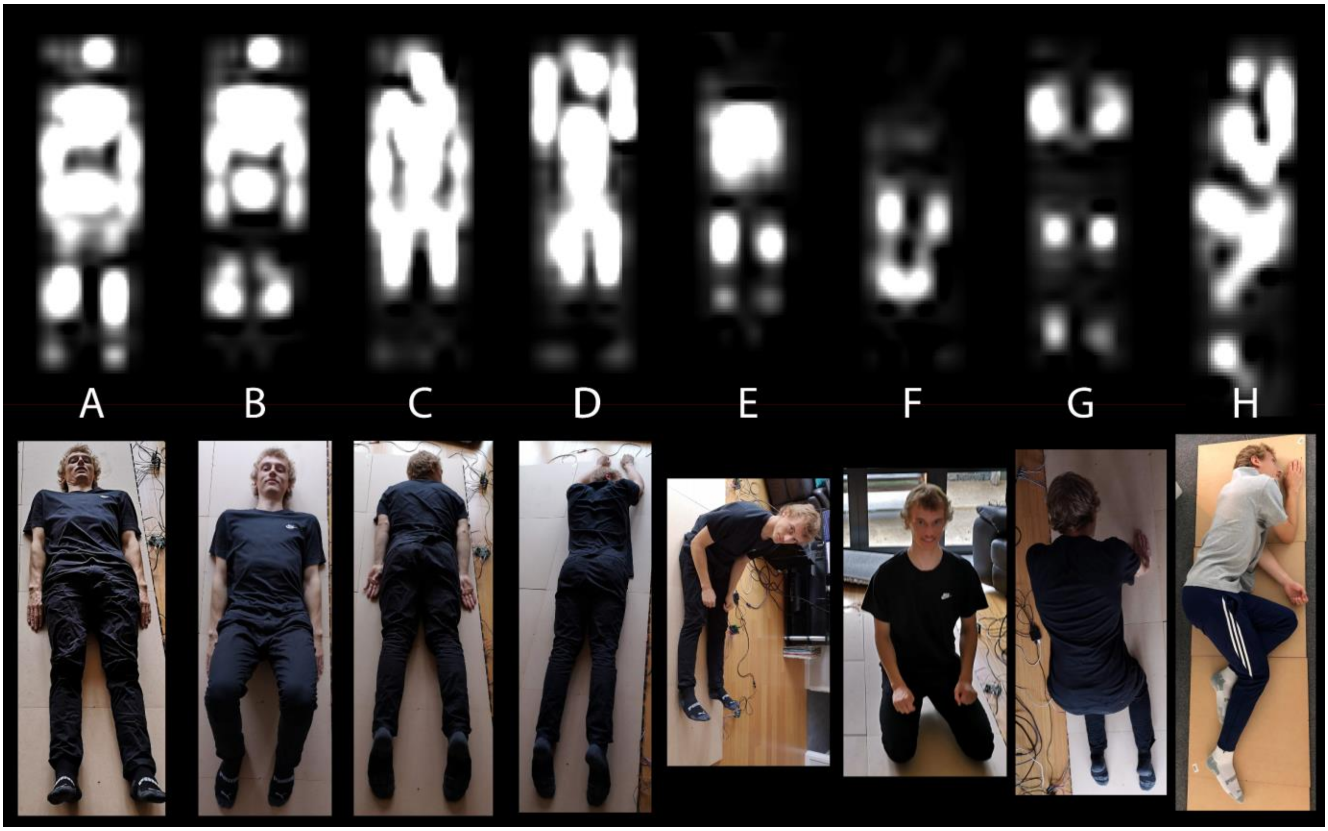

FIGURE 14. A subject in a variety of poses upon the floor.

compared to the thickness of the footwear. As can be observed, the localization error for subject 2 with thinner footwear is higher than that for subject 1 with thick shoes.

Tables 1 & 2 compare the localization accuracy of CapLoc against the state-of-the-art floor-based and other DFL systems. As can be seen, the proposed system is more accurate than other systems reported in the literature. CapLoc's accuracy is likely to be even higher than that which is being reported if the ground truth of the foot could be more reliably established. The problem with placing the tracker on the foot is that it can lose line of sight with the light houses. In such a scenario, the ground truth recording system loses calibration (as discussed earlier), reporting incorrect positions. Therefore, a practical compromise was made. It should be noted that, if a person is not in contact with the floor, they are not visible to CapLoc. However, in a real-life setting, people can only enter and exit a room at defined points. They can be tracked around the room and if they remove themselves from contact with the floor (e.g. by sitting on a chair) they can be assumed to be in that location until they are seen again (i.e. they stand up from the chair).

IV. POSES CAPTURED BY CAPLOC FOR FALL DETECTION

Fall is a major health risk for the elderly, negatively affecting their health and quality of lives. It poses also significant burden on the healthcare and elderly-care institutions. For someone living alone, timely and accurate fall detection is needed to initiate swift medical assistance.

Personal Alarm System (PAS) can be worn by an elderly person. In case of any problems (e.g., a fall), it enables the alarm activation by just pressing a button. Unfortunately, if the victim loses consciousness or is in a confused or panicked state, the button may not be pressed [54].

Wearable sensors, utilizing primarily accelerometers (e.g., presented in [55]) have been proposed for automated fall detection. However, they rely on the subject to wear a sensor at all times. Such a wearable device can be forgotten or misplaced or get damaged. It also requires charging or battery replacement that again can be missed. There may also be a reluctance from a person to wear the sensor. Smartphone-based fall detectors (e.g., discussed in [56]) are also associated with similar issues. Camera- [57] and sound- [58] based fall detection approaches are perceived to be invasive to privacy. Wireless- [59] and IR- [60] based systems rely on anomalous activity detection. They utilize the signatures for a fall that are not immediately obvious to the naked eye [61]. Large amounts of data are generally required to train a model to detect falls. However, the falls are rare events. Besides, it is very difficult to simulate them with human participants. All of this makes it hard to collect enough data to train a robust classifier for fall detection [62].

When using CapLoc, a simple and more naive algorithm potentially could be used for fall detection. For example, a sudden increase in the area of contact with the floor could suggest that a person has gone from a standing to a prone position. By combining it with pose capture and temporal

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changes in the pose, it could be possible to detect an event such as a fall. Rather than trying to detect a rare, anomalous event, CapLoc can support a fall detection approach identifying the immediate aftermath of the fall, i.e., the subject lying on the floor.

A. LYING SUBJECT POSE CAPTURE

An investigation was undertaken to determine if different poses can be observed by using CapLoc. A subject laid on the floor in eight different poses, with the system output being recorded. The following poses were tried (Fig. 14): A – the subject was lying face up with the arms by the sides and legs flat; B – the subject was in the same pose except with the knees were in the air and the feet whilst still on the floor wre close to the body; C – the subject was lying face down with arms by the sides; D – the subject was lying face down with arms stretched above the head; E – the subject was sitting upright with the legs outstretched in front; F – the subject was kneeling; G – the subject was crawling on the hands and knees; H – the subject was lying in the fetal position. It can be seen that the poses were captured reasonably distinctively by the CapLoc.

This suggests that once sufficient data are available, not only fall detection but also fall pose recognition could be achieved while employing relevant classification models (e.g. applying histogram distances [63]).

B. POSE AREA ESTIMATION

Parts of the foot detection algorithm can also be used to estimate the contact area of a subject with the floor. Each individual capacitance reading (represented as a single pixel) is subject to background subtraction, cubic interpolation, and, finally, binary thresholding as discussed before. Each pixel then represents an area of the floor defined by the size of each copper-foil sensor and the interpolation factor. The number of pixels above the threshold then approximates the area of the contact.

Each of the poses in Fig. 14 had their areas estimated by the system to demonstrate the CapLoc potential for fall detection. It can be seen from Table 4 that the poses of the lying on the floor have much larger contact areas compared to a footprint, thus supporting the suggestion that the floor contact area could potentially be used for fall detection.

Certain poses (e.g., G) could be confused for multiple sets of footprints. However, if fall detection is combined with occupancy tracking, it could distinguish the fall from the case of three people standing near each other. People only enter and exit the room at defined points and hence they can be tracked around the room with reasonable accuracy. Therefore, if there is only one person in a room (or in a certain area of it), and an image of a potentially dangerous pose arrives, the system would be able to trigger the fall alarm. A body on the floor will have a significantly larger estimated contact area than a footprint regardless of the size of the body. An abrupt increase in area suggests that a fall may have occurred. Therefore, the

TABLE 4. Comparison of the area of different poses.

Pose	Area (m^2)
A – lying on back	0.64
B – lying on back with knees up	0.54
C – lying on front, hands by side	0.64
D – lying on front, hands above head	0.59
E – Sitting with legs outstretched	0.28
F – Kneeling	0.16
G – Crawling on hands and knees	0.19
H – lying in fetal position	0.58
Single foot area	0.05

difference in body size should not impact the fall detection performance. Also, with large amount of data collected for people of varying body size, sophisticated image recognition techniques (e.g. a deep neural network classifier [64]) could be used in the future to recognize a fall event rather than just using the contact area.

V. CONCLUSIONS AND FUTURE WORK

The developed capacitive floor, CapLoc, can identify the position of a subject's feet and track a single individual while walking upon it. The median and 90 percentile error of CapLoc for a wide-range of trajectories were found to be 0.026 m and 0.066 m. The sample rate used by the prototype hardware was at 10 Hz per individual copper square. A new version of the hardwar e is currently undergoing development. It will offer higher sensitivity and a much-improved sample rate whilst still being compatible with the current flooring tiles as well as signal and data processing techniques. Further work will also help to reduce the stray capacitance by potentially using shielded cabling and to improve the background capacitance measurement.

The localization experiments were performed with a single person on the floor. However, it was demonstrated that the system was capable of detecting multiple targets simultaneously. For ambient signal based DFL techniques (e.g. wireless or IR), each subject adds interference and lowers the SNR leading to poor performance. In contrast, subjects on CapLoc that are spatially separated do not interfere with each other. Therefore, by dividing the floor into sperate smaller areas, it is possible to track targets within those spaces using the algorithm outlined in this paper. It can be further improved by incorporating a particle filter or some similar techniques. However, tracking multiple targets in a crossover scenario, where targets come together and then diverge, will require user identification. It was found that CapLoc systematically overestimates the foot area. However, such overestimation occurs uniformly around the foot perimeters. As such, it did not affect the position of the center of the foot. Unfortunately, the overestimation phenomena means that it would not be achievable at this stage to accurately identify individuals based on their estimated footprint area. However, it is possible to discern the different phases of a subject's footstep on CapLoc from the initial heel strike, through the midstance to the toe-off. During this sequence of events, the center of contact of the foot moves from the heel to the toe. With the improved hardware, in combination with other features (e.g., stride

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length and foot angle) future work will also explore the identification of individuals using their gait patterns. In order to achieve this, significant data needs to be collected to train a machine learning algorithm [65].

Only flat footwear was employed during the experimental investigations while showing good results. Future investigations will also include performance evaluation of the proposed technique on a variety of footwear types (e.g., footwear with raised heels).

Finally, poses of a subject lying on the floor subject can be clearly captured for a variety of positions. Therefore, the proposed technique has the potential to be applied to develop an accurate yet noninvasive fall detection system. Future work will involve collecting sufficient pose data from multiple subjects of varying body size. These data can then be used to train a classifier to detect poses and subsequently identify the fall occurrence.

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