Counting Multiple People on a Floor Based Array Sensor System

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Abstract – We have developed a context-aware system that uses the functionality associated with the Internet of Things (IOT). We have a floor based array sensor system, which we call the Smart Carpet, which recognizes a person walking or falling, reports the fall and stores the data for regular evaluation of the gait parameters. These all have medical benefits. Here we report the improvement, which counts the number of individuals walking on the carpet. We used two methods to perform the count; the number of active sensors at given time, and the number of unique subgroups formed by the activated sensors using the connected component labeling algorithm for varying number of frames in the sliding window mainly 3, 5 and 9 frames. Our results showed that we could count and monitor individual and multiple people walking on the carpet with an average accuracy of 100\%. We use the carpet as a component of an automated health monitoring system, which helps enable independent living for elderly people and provide a practical smart home environment that improves quality of life, reduces healthcare costs and promotes independence.

Keywords: Sensing Floor, Patient Monitoring, Detecting People, Data Acquisition, Data Mining, Internet of Things (IOT), Smart home.

1 Introduction

The number of people aged 65 and older is growing worldwide. The US population will have one in five people 65 or older by 2030 [1]. The research community is innovating new technologies to help assistive living. However, the challenge is to have unobtrusive and user-friendly, unobserved, hand-free and affordable system that supports assisted living of elderly in their homes or in nursing houses.

Systems have been proposed and developed which can be categorized into wearable (accelerometer and gyroscope) [2], and non-wearable (context-aware) [3,4,5,6,7,8]. These systems can be used to detect falls, estimate gait, monitor elderly activities. In addition, they can recognize, count people, and monitor their activities.

Wearables sensors systems are effective devices to detect and recognize the location and activity of people. However, they are obtrusive, must be worn at all times and need continuous power (batteries). In addition, it is not possible to anonymously count and detect people without previous knowledge of the person’s wearable device.

Alternatively, context aware systems overcome some of these issues. In video monitoring systems, the vision techniques filter the images at the device level due to privacy concerns. However, the users still have the feeling that of being watched. Kinect, a video-based system uses skeleton tracking to detect people with good resolution has value [9, 10]. However, it suffers degraded performance with occlusion, and limited depth range. Multifunction radar systems [11] proved to be promising solution in detecting humans and their activities even behind walls or foliage, yet they suffer classifications accuracy for other barriers and movement gestures. Microphone array sensors [7, 12] suffer from noise and multiple interference.

Our lab uses context-aware, non-computer-vision based human recognition and fall detection system. It is a floor based array sensors system, i.e. smart carpet [13], which is completely private. One installs it in the home or apartment and additionally has usefulness in places where traditional sensing system might suffer complications like occlusion. The smart carpet system includes the sensor data acquisition, data manipulating, data reading, storage, display, and communication. The system operates by detecting the person’s movement and storing the floor sensor data. The motion on the carpet activates a set of sensors that outputs a voltage signal. The system amplifies the signal, digitizes it, and then translates it into a frame for further processing. We ran computational intelligence algorithms to measure and estimate people’s gait, and detect falls. Our goal is to accurately recognize, count and monitor the movements of the individuals walking on the smart carpet system.

We organized this paper as follows. First, the methodology, which includes an overview of the system we developed and installed in lab settings. We describe algorithms used to count the number of people walking on the carpet. Third, we show experimental results for different walking scenarios performed by volunteers. Finally, we discuss the achieved results, limitations and future work.

2 Methodology
2.1 System overview

The smart carpet system, as shown in Figure 1 consists of the Smart Carpet sensors laid under the mat, data acquisition system, and processor. The signal scavenging sensors connect to the data acquisition system that scans at configurable speeds depending on the size and number of sensors. Signals convert to digital values using 10-bit Analog to Digital convertor, and microprocessor further thresholds providing a 1 for activated and 0 for not activated sensor, as well as formatting the frame with an S for start and E for end. A computer then reads this scan as an ASCII frame. The software components process the data frames, and use different computational intelligence methods to perform the required operations like fall detection, gait estimation, data visualization, and notification. Additionally, the system can show the signal data scavenged by the sensor for fine-tuning of the system parameters. The system consists of sensor array made into four segments A, B, C, and D. Each segment has 32 sensors; segment D was turned off for this project, and the sensors in each segment connects to the data acquisition system. Figure 2 shows the layout of the carpet segments. Walking across the carpet from A to C or C to A (Longitudinal Direction) will require longer time, longer travelled distance, and more activated sensors count, compared to waking from segment D direction bottom up (Transverse Direction). We made use of a binary display of the activated and non-activated sensors on the carpet to see the traversal of the individuals.

2.2 Experiments and counting algorithms

We collected data from four different people. As listed in Table I, each person, individually, performed 10 walk trials in traverse direction from bottom of segment A then to segment B and back to the beginning. Then, multiple persons participated in 2 people, 3 people and four people walk trials for 10 times each.

The smart carpet data acquisition system scans the carpets at 9 frames per second. Each frame consists of 128 sensors, where all segment D sensors turned off. However, we used them to build 12x12 binary image. Where ‘1’ means, the sensor is activated, and ‘0’ means it is not activated. This image becomes the base data structure to perform computation to recognize people on the carpet. We used Connected Component Labeling (CCL) algorithm as described in [14], we applied the same procedure for both single frames and window size of frames encompassing variable number of frames: 3, 5, and 9. Each window corresponds to time (WS = 3 frames correspond to 0.2 seconds, WS = 5 frames corresponds to 0.5 seconds, and WS = 9 frames corresponds to 1 seconds) WS = total number of frames corresponds to total travel / ambulation time). We used to 8-connect neighborhood [15] for our experiments to ensure we do not ignore the effect of interference among the sensors, and so we have biased results. We used a hybrid model of both the number of subgroups formed by the neighboring activated sensors, and the count of the subgroups formed by individual activated sensor that are not direct neighbors (outside the 8 neighborhood).

Another method we used is the count of the total sensors activated for full walk, and then divided by the average

<table>
<thead>
<tr>
<th>Subject</th>
<th>Weight</th>
<th>Height</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male – Adult</td>
<td>200 lb, 90.72 Kg</td>
<td>5’9”, 174 cm</td>
<td>40</td>
</tr>
<tr>
<td>Female- Adult</td>
<td>150 lb, 68 Kg</td>
<td>5’3”, 160 cm</td>
<td>31</td>
</tr>
<tr>
<td>Female- Child</td>
<td>98.4 lb, 44.63 Kg</td>
<td>4’8”, 142 cm</td>
<td>12</td>
</tr>
<tr>
<td>Male - Child</td>
<td>49.7 lb, 22.5 Kg</td>
<td>3’11”, 119 cm</td>
<td>8</td>
</tr>
</tbody>
</table>

Table I Subject’s Age, Weight, and Height
number of sensors activated per individual(s) who performed the walk. For example, the "Two people walking in opposite directions", we took the average count of active sensor performed by the two people when they walk alone on the carpet, and then divided the total active sensors of the full walk by this average number to count number of people.

3 Experimental Results

We performed 10 experiments for each scenario: individual, two people (same and opposite directions), Three people (same direction), and four people (same and opposite detections). Figure 3 shows the binary image of the carpet layout for “Two People Walking in Opposite Directions” scenario. It took 4 seconds to perform the walk. The left image shows the start of the walk (t = 1 second). Two people walk in Opposite directions: Longitudinal Direction (A <-> C), frames are grouped in a window of size 9 frames/sec (i.e. 1 second ambulation time). All sensors in Segment D are turned OFF. This applies for all experiments and results.

Figure 3  Active sensors map: Two people walk in Opposite directions: Longitudinal Direction (A <-> C), frames are grouped in a window of size 9 frames/sec (i.e. 1 second ambulation time). All sensors in Segment D are turned OFF.

Figure 4  Active sensors map: Two people walk in the Same directions: Transverse Direction (A ↑ B), frames are grouped in a window of size 9 frames/sec (i.e. 1 second ambulation time). Segment D sensors turned OFF.

Figure 5  Active sensors map: Four people walk in Opposite directions: Longitudinal Direction (A <-> C), frames are grouped in a window of size 9 frames/sec (i.e. 1 second ambulation time). Segment D sensors turned OFF.
The computational algorithm ignores these individual sensors. Hence, we got two subgroups. The Right image represents the full walk and shows the path that each person followed. Figure 4 shows the binary image for the orthogonal “Two People Walking in the Same Direction” scenario. It took 4 seconds to perform the walk. The left image shows the start of the walk (t = 1 second). Two subgroups of size 3 each (three connected neighbors) are shown. The middle image shows the subgroups at the end of the walk (t = 4 seconds), with one subgroup of size one, and one subgroup of size three. If the computational algorithm ignores the individual sensors, then the middle image would show only one person. However, the speed of walking of the two persons is different and hence one finishes before the other. So, if we change the time frame we would see the second person. The Right image represents the full walk and shows the path that each person was in a contiguous segment meaning the distance between the two segments is of one foot, and hence some sensors got activated due to interference. If Person 2 walks on Segment C, which is greater than five foot apart, such behavior did not exist. For example, the opposite scenario shown in Figure 3 does not have this problem. In Figure 4 five people walk in opposite directions. At the start of the walk left the persons were at separable distance. They were recognized and by their own subgroup. However, as shown in the middle, they became closer and were not clearly separated. Then when they reached the end of the walk, right, they were again separable. Figure 6 shows full walk image, all activated sensors during the walk, for more walk scenarios (three and four people in the same directions, and four people in the Opposite directions). We further studied one scenario for two, three and four people walking in the same direction (transverse direction). We ran the hybrid algorithm for different window sizes of frames. We applied the algorithm for 10 walk trials. Figure 7 (a,b,c) shows the count of people for “two people walking in same direction”, “three people walking in same direction”, and “four people walking in same direction” scenarios for different sliding windows of frames. Results showed that we could reliably count the number of people for the “two” and “three” people scenarios. However, when number of people increased for the same size of the carpet used, it became difficult to count the people reliably (accuracy of 20%). Accuracy is proportional the ratio of the number of people walking on the carpet and the carpet size. We could not determine the optimal window size of frames that fits all scenarios, especially when the ratio of the number of people to the carpet size is big. Figure 8 shows that the count of people for two, three, and four people walking in the same direction at window size of nine (WS = 9 frames, i.e. the algorithm determines the count of people at time intervals of one second). As Figure 8 shows that at WS = 9 frames, the accuracy of counting people is 100% for two people, 90% for three, and 30% for four people.

We evaluated the binary image by the count of the ‘1’ pixel value, which corresponds to an active sensor. Figure 9 shows the path we used to identify the average number for activated sensors for the four persons who performed the experiments. TABLE II shows the activated sensors count for each scenario, and the average time it took to perform the scenario. It is clearly evident that the bigger the area is the more people walking on the carpet. The count of the active sensors is 72 rounded to whole number. Comparing this to the 58 for the same number of people but in the same direction. The carpet layout and the time spent for the opposite directions (6 seconds) activate more sensors than and the same directions (4 seconds) of walking on the carpet. We calculated the average number of sensors activated by each walk. We then divided by the mean of active sensors produced by individual walks for the persons who performed the walk. We rounded the result to obtain the count of people. This allows us to determine the count of unknown people walking on the carpet. TABLE III shows the count of people using the average active sensors count, per individual(s) performing the walk trials, as the denominator for the total active sensors in the full walk trial.
Discussion and Conclusion

In this paper, we extended the functionality of the smart carpet to count the number of people in addition to fall detection and gait estimation. Falls for an individual are a rare but high impact event, and effect a large fraction of the population. So, it is important to monitor, but not act until necessary. Further, the system generates data 24/7 and so stored for later analysis to detect changes in gait. Since a plurality of people walking on the floor can mimic a fall event, it is important that the system distinguish between a plurality of people and a fall event. We monitored the activity of volunteers walking on the carpet. Our algorithms were able to count the number of people at any given time with an average accuracy of 100%. This result affected by the number of people walking, and the spatial distance that separates them, and by the ratio of the people walking to the actual carpet size. The bigger the ratio the lower the counting accuracy. We used the total count of activated sensors compared to the average of individual walks sensors count.

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and were able to count the number of people with close 100% accuracy.

Our results show high performance count and detection accuracy. Since our algorithms do not depend on the spatial location or dimensions of the sensors on the floor, we can count and track people on any sensors distributions. Future work will involve using the centroid in two settings; the directions of the centroid of the connected component, and, spatially, by computing the centroid of the actual dimensions minimum distance by which we recognize different people. We believe more information can be deduced using this technique like gait parameters (walking speed, stride length, and step length).

5 References


<table>
<thead>
<tr>
<th>Walk Scenario</th>
<th>Average active sensor s count</th>
<th>Average active sensors count for persons who performed the walk</th>
<th>People Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>One Person</td>
<td>13.62</td>
<td>13.62</td>
<td>1</td>
</tr>
<tr>
<td>Two persons- Same direction</td>
<td>27</td>
<td>14.20</td>
<td>2</td>
</tr>
<tr>
<td>Two persons- Opposite direction</td>
<td>25</td>
<td>14.20</td>
<td>2</td>
</tr>
<tr>
<td>Three persons - Same directions</td>
<td>49</td>
<td>14.10</td>
<td>3</td>
</tr>
<tr>
<td>Four persons - Same direction</td>
<td>58</td>
<td>13.62</td>
<td>4</td>
</tr>
<tr>
<td>Four persons - Opposite direction</td>
<td>48</td>
<td>13.62</td>
<td>4</td>
</tr>
</tbody>
</table>


