Floor Based Sensor System: Additional Intelligence, Gait Estimation, and Scavenging Charging Characteristics

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Abstract - *In this paper we propose further in-depth analysis to our smart carpet, a floor based personnel detecting system. We have added more intelligence by enhancing fall detection algorithms. Both a convex hull, and heuristic algorithms were developed to detect falls. The proposed algorithms detected fall with 95% sensitivity and 85% specificity when combining both methods exclusively. We extracted and estimated gait parameters, comparing our system to the GAITRite system, which is used as gold standard; here we investigate whether the differences between the two systems are statistically significant. The Statistical T-Test showed excellent agreement between the smart carpet and the GAITRite in estimating gait parameters. With (P = 0.55), the walking speed differences of the two systems are not statistically significant. Additionally we studied the characteristics and the behavior of the sensor's scavenged signal. We designed and built a single large sensor, where subjects performed multiple walks on the sensor, and their data recorded and studied. The sensors' voltage waveforms behaved differently corresponding to different people and set of walking trials. The covering material, and the environmental conditions affect the behavior of the scavenged signal. More detailed study and experimental trials are needed.*

Keywords: Signal Scavenging, Fall Detection, Gait Estimation, Sensor, and Eldercare

1 Introduction

Research focused on older adults continues to promote successful aging, especially regarding how to enhance the overall quality of life and provide adequate medical care while keeping health care cost under control. Technology is a welcome addition to the population of the elderly; it offers the elderly full productive and independent lives [1].

The continued increase in longevity will yield a steep rise in the old-age dependency ratio, defined as the ratio of the number of elderly people to those of working age. This ratio is expected to double from 11.7% to 25.4% in the next 35 years [2]. The number of people aged 80 and over is going to triple in the next 35 years [3]. Approximately 28-35% of people aged 65 and over fall each year increasing to 32-42% for those over 70 years of age [4]. Severe fall injuries can also lead to deaths [5]. Several studies have shown that better outcomes are correlated with rapid initiation of medical intervention immediately after a fall [6].

Research, then, to develop new technology or enhance existing ones to detect falls and can help reduce the consequences of a fall. All fall detection systems have a common objective; to distinguish a fall from activities of daily living, which tends not to be an easy problem to solve. However falls to an individual is a rare event even though the elder population fall frequency is high. Fall prediction or fall risk analysis extends the functionality of smart carpet by extracting and estimating Gait Parameters[7]. Recent research shows that change in gait parameters may be predictive of future falls and adverse events in older adults such as physical functional decline [8-11] and fall risks [12-14].

Privacy is major concern, so there is a need for context-aware sensor systems that passively detect human presence or activities. Multiple passive systems were developed to detect falls [15-21]. Each of these systems has limitations and/or complex implementation, and high cost. Our system, the smart carpet, is designed to scavenge the signal from the environment. The sensor made from a conductive material picks up stray 60 Hz noise to detect presence of the person without much complexity [22-25].

This paper describes development in fall detection algorithms, analysis of the gait estimating system, and study of the charging characteristics of the scavenged signal. Section 2 of this paper provides an overview of the system, and our methodology. Section 3 contains the experimental results. Finally, the major points of this paper are discussed along with future work.

2 Methodology

2.1 System Overview

Our system, as shown in Figure 1, consists of the Smart Carpet, which is a floor based personnel detector, data acquisition system, and processor. The signal scavenging sensors can be built and produced in different sizes and shapes. All sensors function the same. The sensors are connected to data acquisition system that scans at configurable speeds depending on the size and number of sensors in one segment. Signals converted into digital values with a constant threshold using 10-bit Analog to Digital convertor, and then read by a computer 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.

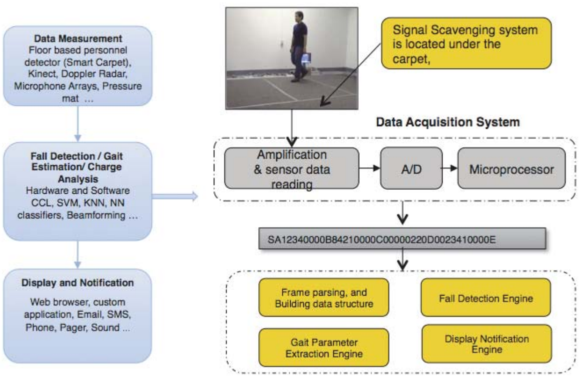


Figure 1 System overview

2.2 Fall Detection

In order to detect falls, we need to detect motion on the carpet. To achieve this goal, we built sensors and organized them into 4 segments with 32 sensors each. The data acquisition system in Figure 1 reads a total of 128 sensors. After a person walks or has mobility on the carpet, the voltage generated by the sensors that exceeds certain threshold, determined experimentally, is considered active. As more motion occurs on the carpet more sensors become active. In this experiment, we have 10 volunteers each of them performed 8 walk-fall patterns. The falling patterns adapted from previous work by our eldercare technology research group [26]. Figure 2 shows the walk-fall pattern. Each rectangle represents a set of frames (each frame resulted from one complete scan of the 128 sensors). Recorded videos used as gold standard to verify the accuracy of the fall detection algorithms. In [25] we used different algorithms and sliding window with different sizes (*WS*) sizes to determine the fall. Later, the data used to train a classifier and add intelligence to the system. In this paper, we will discuss two algorithms developed and enhanced to help detect falls; convex hull area, and active sensors count given certain active sensor layout; we call the later method "Heuristics".

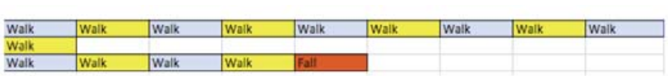


Figure 2 Walk-Fall pattern: Each rectangle represents one frame

2.2.1 Convex Hull Method

In convex hull area algorithm, we used a window size of number of frames (sliding window of size *WS*) to form an array list of active sensors, and then apply the quick convex hull algorithm [27]. We found the points forming the convex hull (polygon) for the set of active sensors on the carpet. We calculated the area of the polygon according the shoelace algorithm [28]. To detect a fall, we run the algorithm for different window sizes (*WS*) and thresholds (*TH*). In Figure 2 above each colored cell represents a sliding window of size *WS*; *WS*= 1,2,3,4 ...etc. So we group the active sensors and then apply the algorithm. Having a constant Threshold (*TH*) with changing (*WS*) didn't give good result. Our approach is to make the threshold variable based on the number of active sensors forming the hull. The new threshold is given by the equation:

$$TH = WS * HS * \alpha_{HULL} \tag{1}$$

WS: the sliding window size,
HS: number of points forming the convex in a *WS*.
$\boldsymbol{\alpha_{HULL}}$**:** constant determined experimentally= 0.3

2.2.2 Heuristic Method

In heuristic algorithm, we converted the array of sensors data into a matrix format. Then we counted the number of active sensors that are contiguous, as shown in Figure 3, in a row or column. We determine the fall if the count meets or exceeds some threshold (*TH*). The Threshold is given by the equation:

$$TH = WS * \alpha_{Heuristic} \tag{2}$$

WS: the sliding window size,
$\boldsymbol{\alpha_{Heuristic}}$**:** constant determined experimentally= 1.2

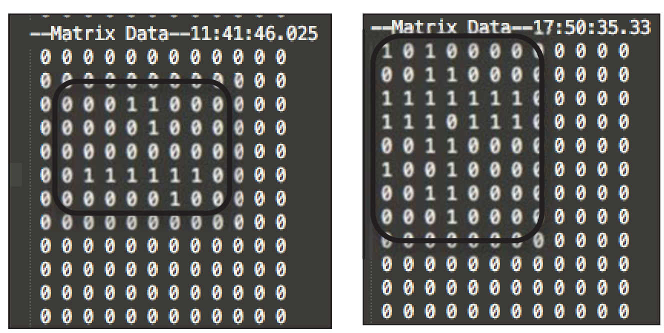
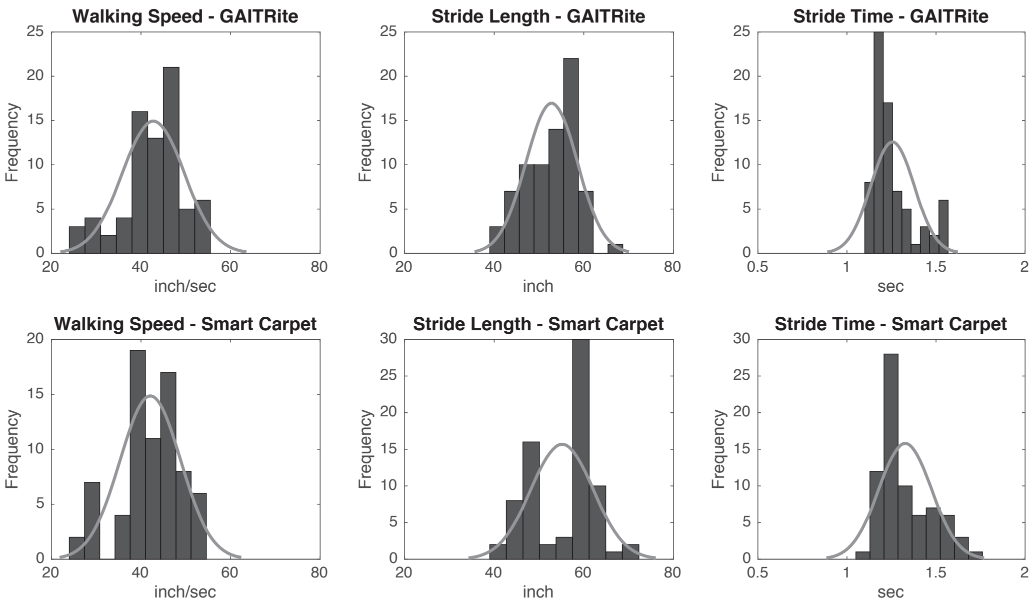


Figure 3 Data Matrix samples for Heuristic algorithm

2.3 Gait Estimation Performance

In pervious work [6], we used the smart carpet to estimate the gait parameters of walking speed, stride time, and stride length. We measured the distance travelled, and



elapsed time. We computed the number of footfalls. We used these parameters to estimate the gait characteristics of the persons walking on the carpet. Results showed that we could extract and estimate the parameters with acceptable relative error within acceptable standard deviation. Nine subjects participated in the experiment. Each subject was tested multiple times, trying to maintain same walk pace. In total, there are 75 walk sequences. Subjects normally take about 5-10 steps to complete the walkway. In this paper, we are interested in measuring how much our system matches the GAITRite; the gold standard for gait measurements. TABLE I shows the mean, median, standard deviation and standard error for walking speed, stride time, and stride length of the data resulted from the 75 walk sequence. Figure 4 shows the histogram of walking speed left (top, and bottom), stride length middle (top, and bottom), and stride time right (top, and bottom), fitted with normal distribution function.

TABLE I. MEAN, MEDIAN, STANDARD DEVIATION , AND STANDARD ERROR FOR 75 WALK SEQUENCE

	Mean	**Median**	**Standard Deviation**	**Standard Error**
Walking Speed				
GAITRite	42.7666	43.1299	6.9181	0.804
Carpet	42.0995	42.6457	6.7559	0.785
Stride Time				
GAITRite	1.2557	1.22	0.1221	0.014
Carpet	1.3268	1.27	0.1475	0.017
Stride Length				
GAITRite	52.8381	54.9075	5.7459	0.668
Carpet	55.1429	58	6.9634	0.809

We used different statistical tests to measure how well the two systems match, and whether the differences between the two systems are statistically significant or not statistically significant. Using the two-sample t-test (***ttest2***), a t-test returns a test decision for the null hypothesis that the data in GAITRite and smart carpet comes from samples from normal distributions with equal means [29]. The returned value of $\mathbf{H_0}$ = 0 indicates that ttest2 does not reject the null hypothesis at the default 5% significance level. The alternative hypothesis is that the data in GAITRite and smart carpet comes from samples with unequal means. The result $\mathbf{H_0=1}$ if the test rejects the null hypothesis at the 5% significance level, and 0 otherwise. The *p-value* is the probability of observing a test statistic as extreme as, or more extreme than, the observed value under the null hypothesis. Small values of p cast doubt on the validity of the null hypothesis. A Mann-Whitney U-test, also called the *Wilcoxon rank sum test*, is a nonparametric test that compares two unpaired groups. It ranks all the values from low to high, paying no attention to which group each value belongs. The smallest number gets a rank of 1. The largest number gets a rank of $\boldsymbol{N}$, where $\boldsymbol{N}$ is the total number of values in the two groups. If the means of the ranks in the two groups are very different, the *p-value* will be small. It tests the null hypothesis that data in GAITRite and smart carpet are samples from continuous distributions with equal medians, against the alternative that they are not. Additionally, we calculated strength of linear correlation, and fluctuations of one of the system with respect to the other by computing the *correlation coefficients*, and the coefficient of determination (***R-squared***) respectively for Walking Speed, Stride Time and Stride length [31].

2.4 Signal Scavenging Charging Characteristics

Signal scavenging originated from the concept of energy harvesting from the existing energy in the environment. Our sensor system is scavenging energy from 60 Hz stray electromagnetic waves. When a subject steps or walks on the sensor, a change in the total charge of the sensors occurs causing the generated voltage level to increase and decrease depending on the step in or out of the sensor. The shape of the waveform, the amount of charge accumulated or discharged during this process is of interest. In previous work; fall detection and gait estimation, we were interested on whether the sensor is active or not. However, we believe there may be more information in the scavenged signal. We investigated some of the characteristics of the sensor's accumulated charge or voltage level with the hope to answer the question: *What other information can we get from the walk?*

To achieve this goal, we developed a new sensor segment 8 feet long and 18"wide. As listed in

TABLE II; four different people in terms of gender, weight, height and age walked on the sensor segment four times each maintaining same waking speed and pace. The generated signal is recorded and saved using MSO4034 Tektronix Oscilloscope for further analysis. We applied proper signal processing techniques; computing the signal's spectral density (Fourier transform), total power, the width and duty cycles. Subjects performed walking trials in different settings: Bare foot, and with shoes. Also, the sensors were covered by threaded carpet, or vinyl material. All walks for given setups were performed at the same time to reduce the effect of the weather conditions: temperate and relative humidity. These environmental conditions have effect on static charge build.

TABLE II SUBJECTS' AGE, WEIGHT, AND HEIGHT

Subject	Weight	Height	Age
Male – Adult	200lb, 90.72 Kg	5'9",174 cm	40
Female- Adult	150 lb, 68 Kg	5'3",160 cm	31
Female- Child	98.4lb, 44.63 Kg	4'8",142 cm	12
Male - Child	49.7lb, 22.5 Kg	3'11",119 cm	8

3 Experimental results

Here we show the results of the improved fall detection algorithms. Additinally, we show how well the smart carpet estimated gait matches the GAITRite, which is used as gold standard for gait measurements. Finally, we show the wavefrom generated by the activating the sensor, and it's charging profiles.

3.1 Fall Detection Algorithms

We measured the performance of the fall detection algorithms by counting the number of fall patterns that were detected as falls and we provided both the sensitivity, and specificity of the detected falls on all patterns done by 10 volunteers. TABLE III shows the sensitivity and specificity for the two methods and their combinations. It also shows the configurations; windows size (WS), and threshold (TH) used for the decision. The best results of 95% sensitivity and 85% specificity were achieved using WS= 7, α = 0.3, and 1.2 for Convex Hull and Heuristic methods respectively. Clearly combining the two methods increased the true negatives (TN).

TABLE III. THE PERFORMANCE (SENSITIVITY , SPECIFICITY) OF THE FALL DETECTION ALGORITHMS.

Algorithm	Fall Detected as Fall (Sensitivity)	No Fall detected as No Fall (Specificity)
Convex Hull Area	90 %	80 %
Heuristic	86 %	80 %
Convex Hull AND Heuristic (Inclusive)	75 %	89%
Convex Hull OR Heuristic (Exclusive)	95 %	85%
Threshold criteria: WS=7, α_{Hull} = 0.3, $\alpha_{Heuristic}$ = 1.2		

3.2 Gait Estimation System Performance

The t-test shows how well the smart carpet gait estimating system matches the GAITRite system. TABLE IV shows the statistical t-test2 for the smart carpet and the GAITRite systems. The *p-value* for walking speed is 0.55, which means that the two systems are not statistically different. However, for Stride time p = 0.0017, which means that the differences are statistically significant. This is due to the method we measured the stride time and length; time of first heel stride, or full foot on carpet. We believe a higher resolution sensors will enable us to obtain better correlation and significance measures. Similarly using the Mann-Whiteny U test; The *p-value* is 0.45326 for walking speed, which means that it is not significant at $p < 0.05$. And it is significant for the other two parameters.

TABLE IV TTEST2 - STATISTICS FOR WALKING SPEED, STRIDE TIME, AND STRIDE LENGTH

Variable	Mean	Stdev	T-Test	P	H_0
Walking Speed	42.10	6.8375	-0.5934	0.5538	0
Stride Time	1.30	0.1354	3.1929	0.0017	1
Stride Length	54.91	6.3838	2.1962	0.0297	1

In the scatter plot Figure 5 shows visual of the differences between the two systems. The best fitting line (trendline) with the correlation equations are shown for three gait parameters; walking speed, stride time and stride length. The R-squared of 93% for walking speed shows great agreement between the two systems. Additionally, our calculations showed string relation between the two systems. As expected, the r-squared from Stride time is low meaning more variability between the two systems.

3.3 Scavenged Charge Characteristics

Subjects performed the walks on different sensors surfaces; threaded carpet and transparent vinyl. Results showed sensors covered with different material have correspondingly different signal behavior. The measured

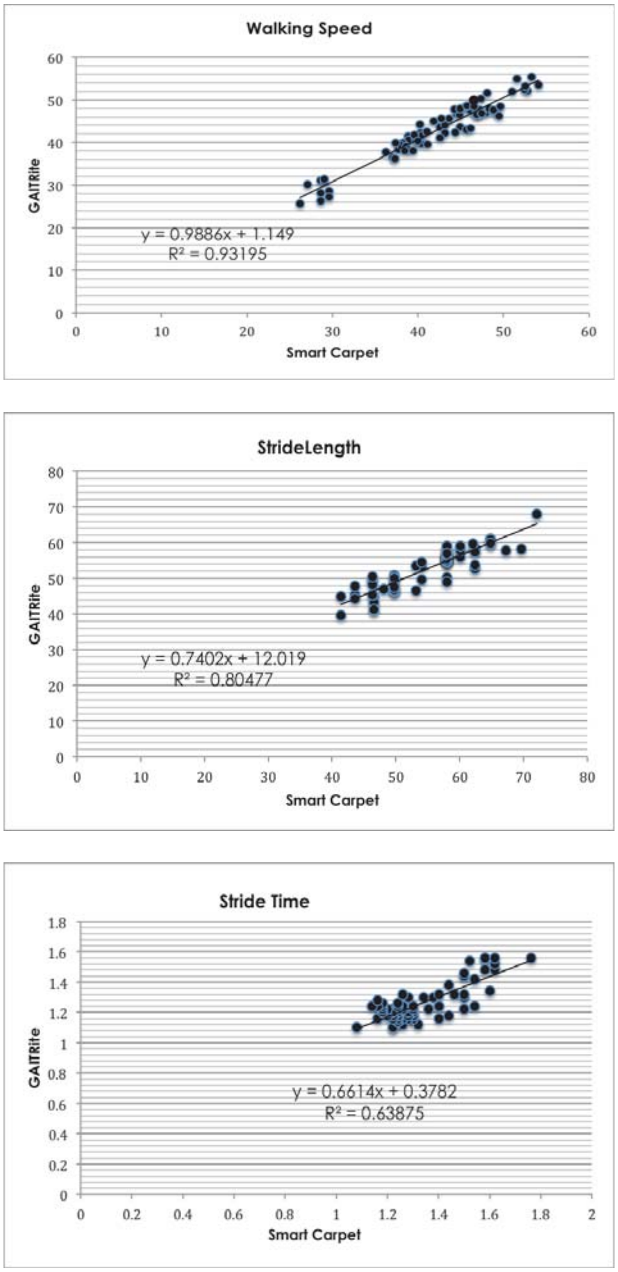


Figure 5 Scatter plot with fitting line and variation factor for both systems with respect to walking speed, stride time and stride length.

power (amount of charge accumulated) differs with different material used. TABLE V shows the average power measured for all four subjects trials on Vinyl and threaded cloth type carpet. Figure 6 shows sample of the scavenged signals from the sensors on both surfaces for a 200lb male, walking on the same 8-foot segment covered by both Vinyl and threaded carpet. This was repeated for 4 subjects, and each subject generated different waveforms. We have traced the footfalls and observed that as the subjects took steps there was charge build up or discharge. The overall droop or in the signal indicated a builddown of total charge as the steps progressed.

TABLE V AVERAGE POWER MEASURED USING VINYL, AND CARPET SURFACES

Subject/Voltage (V)	Vinyl (Power Unit)	Threaded Carpet (Power Unit)
Male – Adult	2543	1620
Female- Adult	951	671
Female- Child	929	162
Male - Child	411	229

However, we need to develop criteria and measurements to understand and interpret the scavenged signal, since different people have different waveforms, and charge build-up characteristics. It seems interesting to investigate considering other factors like weather, shoe type, sensor material...etc.

4 Discussion and Conclusion

The two algorithms; convex hull area, and the heuristic active sensors' count enhanced fall detection for the floor based personnel detection system. Results showed improvements in both the sensitivity and specificity. Most signal scavenging systems, or any signals-based systems are noise prone by nature. Fusing more than one method will help to minimize the effect of the noise on the system performance.

Our system was used to extract and estimate the gait parameters and compare them to the gold standards through the use of GAITRite. Results showed a very acceptable match between the two systems, with 90% correlation, and no statistically difference for walking speed and acceptable margin for stride length. These results are very helpful since of importance is the relative change in gait parameters. In general aging slows a person down and we will be able to detect this slow-down as a change in gait while we keep recording sensor activity 24/7 over a period of years.

Both fall detection and Gait estimation are based on the measured voltage generated by the sensor and whether that voltage exceeded certain threshold or not to consider the sensor active.

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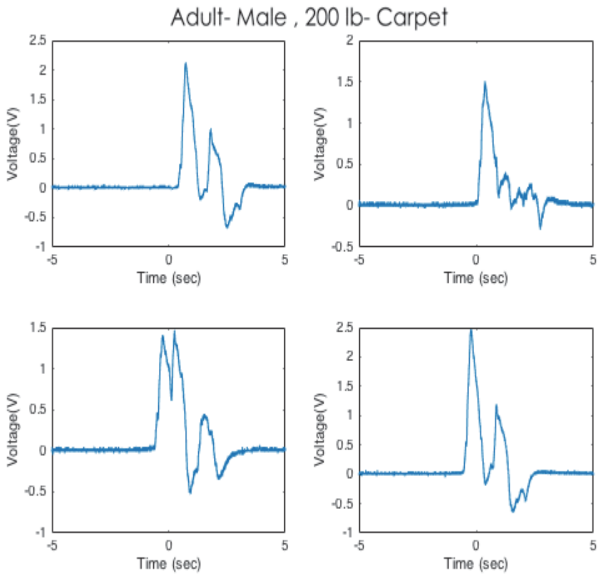
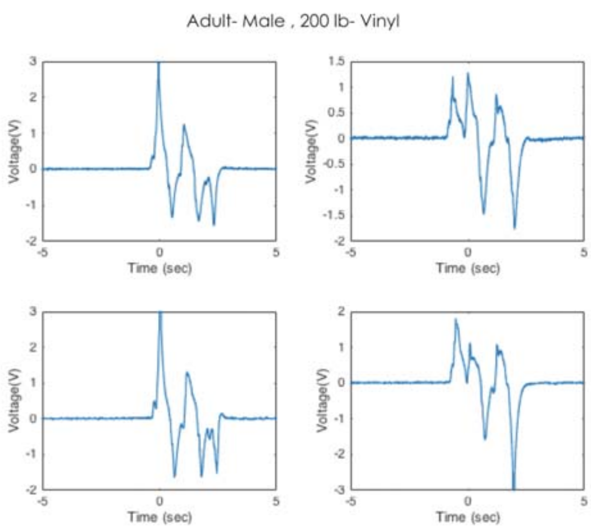


(a)



(b)

Figure 6 Scavenged signals for 200 lb adult male walking on sensors covered by carpet (a) Vinyl (b)

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