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In-Home Floor Based Sensor System-Smart Carpet- to Facilitate Healthy Aging in Place (AIP)

FADI MUHEIDAT[1], (Senior Member, IEEE), AND LO'AI A. TAWALBEH[2], (Senior Member, IEEE)
[1]School of Computer Science and Engineering, California State University, San Bernardino, CA 92407, USA
[2]Department of Computing and Cyber Security, Texas A&M University, San Antonio, TX 78224, USA
Corresponding author: Fadi Muheidat (fadi.muheidat@csusb.edu)

ABSTRACT With the rapidly aging population, there is a need to detect elderly's activity, monitor their health, alert health care personnel, and provide real-time and long-term access to the generated sensor data. With the advances in sensor technologies, communication protocols, computing power, and cloud and edge services, it is now possible to build smart assistive living systems to improve people's lives. In this research, we present a Context-aware and private real-time reporting aging in place system. The proposed system, we call it smart carpet, consists of a sensor pad placed under a carpet; the electronics reads walking activity to provide an automated health monitoring and alert system. We extended the system's functionalities to improve its ability to detect falls, measure gait, and count the number of people traversing the carpet (socializing). In an urgent and time-sensitive situation, we need to provide a real-time notification. We propose a cooperative cloudlet model, where the sensors' data will be sent to the nearest Cloudlet for analysis and extracting real-time decisions in minimal delay. Results showed that our system could assist the elderly in detecting falls with 95% sensitivity and 85% specificity. Measuring and estimating their gait with a mean percentage error difference to GAITRite 1.43% in walking speed; hence, predicting a fall risk and counting people's plurality socializing with the elderly with an average accuracy of 100%. We evaluated our system's improvements in a controlled environment. We are looking forward to deploying the system in a nursing home (after the COVID -19 is over) for more data gathering and validations.

INDEX TERMS Fall detection, gait analysis, context-aware, aging in place, floor-based sensors, intelligent assistive technologies, healthcare technologies, unobtrusive, aging in place.

I. INTRODUCTION

The research focused on older adults promoting successful aging, especially regarding enhancing the overall quality of life and providing adequate medical care while keeping health care costs under control. Technology is becoming essential to the elderly; it offers the elderly productive and independent lives [1]. An apparent goal was to develop new technology or enhance existing ones to detect falls and reduce the consequences of a fall [2]–[4]. All fall detection systems have a common objective of distinguishing a fall from daily living activities, which tends not to be an easy problem to solve. Fall prediction or fall risk analysis extends the functionality of the smart carpet. By extracting and estimating gait parameters, fall risk can be assessed [5]. 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 [6]–[9] and fall risks [10], [11].

Many systems are suitable for clinics or physical therapy centers (GAITRite Electronic mat), another ideal for research labs, and controlled environments like the nursing centers (Vicon motion capture system). Therefore, there is a need to have systems that continuously measure and report gait parameters during everyday activities outside labs. The drawback of lab-specific systems is that the individuals feel instructed to walk in a certain way, in other words, not in their natural daily activity that reflects their actual gait behavior. Many technologies have been studied, developed, and enhanced to be an alternative to the expensive and lab-controlled systems.

Wearable sensors systems that consist of accelerometer and gyroscopes to measure gait parameters have been proposed [12]–[15]. Researchers used different setups, number of sensors, and derived a variety of parameters to assess

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individuals' gait and fall risks with fair agreements compared to gold standards. Some of the wearable's drawbacks are the need to have the individuals worry about charging, wearing or taking off the sensor, and transferring data from the sensor devices. For example, the sensor's position in the smartphone is essential to achieve proper measurement; this will not be possible by only having them in pockets or hands. People with dementia have a limited ability to maintain and use such wearable devices. Studies have shown older adults prefer non-wearable sensors [16] for in-home monitoring.

The Eldercare technology research group at the University of Missouri- Columbia assessed different systems and devices to detect falls, measure gaits, and monitor the elderly's daily activities. They used a low-cost, computer vision-based monitoring system (Microsoft Kinect) [17]–[23]. Its good results and ability to detect a fall, assess gait, and other useful daily living functions may suffer degraded performance with occlusion and limited depth. Floor based sensors that measure the forces applied on the floor are widely spread [24], [25]. In [25], the investigators capture the time-varying signal to measure weight distribution within certain areas. It requires a fixed installation under the metal support structure for the sensors and floor tiles. In [26], they measured the user's foot's ground reaction force by load cells to generate user identification.

Even though technology saves the user's time and health by collecting and accessing shared data, some barriers exist, mainly for the elderly such as usability, cost, and privacy concerns [27]. We developed the smart carpet system to help and support people with dementia or Alzheimer's disease. People who have limited ability to maintain and use wearable devices or showed reluctance to image-based systems due to privacy issues cannot afford high tech and expensive products. Using this floor-based sensor will solve most of the problems mentioned above.

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 [2]–[4], which is obtrusive and preserves privacy. One installs it in the home or apartment and has usefulness in places where traditional sensing systems might suffer complications like occlusion. Continuous tracking and monitoring residents who live alone is essential, as some elderly are reluctant to live in nursing homes. These residents may have visitors, motivating us to expand the smart carpet's functionalities to detect visitors. We developed algorithms to count people's plurality by identifying the activated sensors' subgroups when the individual walks on the carpet.

The extension of the smart carpet system demonstrated here will improve its utility and make the 24/7 monitoring and subsequent storage a valuable, useful commodity. One can envision a future in which monthly evaluation of the smart carpet data will provide gait changes, a record of resident activity, and sociability. We utilized the widespread of smart mobile devices, which are an essential part of our lives nowadays. However, these mobile devices suffer from limited storage and processing capacities. Mobile Cloud Computing (MCC) [26] has become a crucial technology combined with edge computing to provide high performance and cloud services by the offloading tasks to the cloud via wireless networks. To support Aging in Place where real-time processing is required in minimal delay [28], [29]. In Cloudlet based mobile cloud computing, where a cloudlet is a nearby server considered as a cloud resource with a fast network connection [30].

There has been much research interest in activity monitoring, gait analysis, fall detection. We can classify the systems into two main systems: vision-based and non-vision-based. In vision-based systems, researches used and study Microsoft Kinect Systems [31]–[33]. They run different algorithms techniques (Support Vector Machine-SVM, Feed Forward Neural Network- FFNN, Nearest Neighbor -KNN, and Decision Trees) using different features such as vertical velocity and acceleration, adjusted change in the number of elements on the x-y plane after the projection of points below knee height, frame-to-frame vertical velocity (F2FVV), silhouette, curvature scale space, occlusion, and deformation on the joint structure. The non-vision-based systems can be classified into wearables [34]–[37], and context-aware systems [38]–[46]. With all the advantages of portability, mobility comes with some drawbacks; they are bound to the body, held by a hand, suffer battery drain, and require internet or cellular connection to collect sensor data.

In contrast, context-aware devices used where the sensors deployed; examples are smart carpet, pressure mats, piezoelectric polymer, floor vibrations sensor, and others. A more recent trend in assisting the elderly to age in place and present opportunities to reduce healthcare costs is the ambient sensor network. It is a wellness monitoring through daily activity visualization, periodic reporting, and relax-time notification. The system consists of magnetic contact sensors, passive infrared motion sensors, energy sensors, pressure sensors, water sensors, and environmental sensors placed throughout the home [47]. What makes our system different is the low cost and easy to install, multipurpose use, and flexibility in configuration; it can be installed in the restroom floor to ensure privacy compared to the voice or video-based systems.

Our paper is organized as follows: Section II shows our proposed approach. We present the experimental results and discussion in section III. We present our conclusion and future work in section IV.

II. PROPOSED APPROACH

The floor-based sensor 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 with all other bits addressed in a single scan into a frame for further processing. We ran computational intelligence algorithms to detect falls to measure and estimate people's gait and accurately recognize, count, and monitor the individuals' movements walking on the carpet.

The system uses a signal scavenging technique to detect the presence of the person. This technique uses the sensor made from a conductive material to pick up stray 60 Hz noise, which may come from electrical power lines, nearby electrical equipment, and other stray electromagnetic signals. It is challenging to design sensors to deal with very low voltage data because the generated signal always mixes with the unwanted noise signals. Although this strong 60 Hz signal seems to be useless energy, it is a valuable signal source to detect humans' presence and human falls [2]. One installs the sensors for the signal scavenging technique under carpets; it consists of 2 main layers, as shown in Figure 1(a)-(b). The top layer is the sensor layer, and the lower layer is the ground layer. A plastic sheet separates the two sensors and the grounding layers. We used aluminum foil as a sensor. The foil acts as an antenna. In communication, we use both transmitting and receiving antennas. In the receiving antenna, when the electromagnetic signal passes over the antenna, it induces a small voltage and causes electrical energy to flow in the receiver circuitry.

Similar to the antenna, the aluminum foil produces a change in electric voltage corresponding to the change in the nearby electromagnetic field. The peak-to-peak voltage with the activated sensor uses aluminum foil as a sensor, as shown in Figure 1(c)-(d). The voltage level of the 60 Hz signal was measured when somebody touches the sensor (activated). The activated sensor's measured voltage is 300 mV peak to peak, while the non-activated sensor produces about 30 mV peak to peak. When a sensor is not touched or not activated, it picks up a certain level of 60 Hz signal—because the human tissues are lossy media [48], the electric field induced in the human body when the human body is exposed to the electromagnetic field. The body is used as an antenna or medium for signal transmission [49], [50]. The scavenged signal increases when someone makes contact with a sensor or activates it. This because the human body acts as an antenna. As a result, the sensor picks up a stronger signal, detected as a higher voltage signal. The difference in voltage is used to distinguish between activated and non-activated sensors. We used a differential amplifier to reduce the 60 Hz noise impact, as shown in Figure 2 below.

The differential amplifier has two inputs and one output. The first input is for the primary input signal from a sensor, and the second input is the reference signal from a non- activated sensor. The differential amplifier subtracts the signal amplitude of the first input with the second input. Thus, when the primary input sensor is not activated, the primary sensor's noise will be canceled by the second input's reference signal. On the other hand, an activated sensor is the first input with much higher amplitude than the reference input. The subtraction of the activated primary sensor signal from the reference input will still provide a high amplitude signal.

The main configuration required four segments of 32 sensors for a total of 128 input sensors. Each board served one

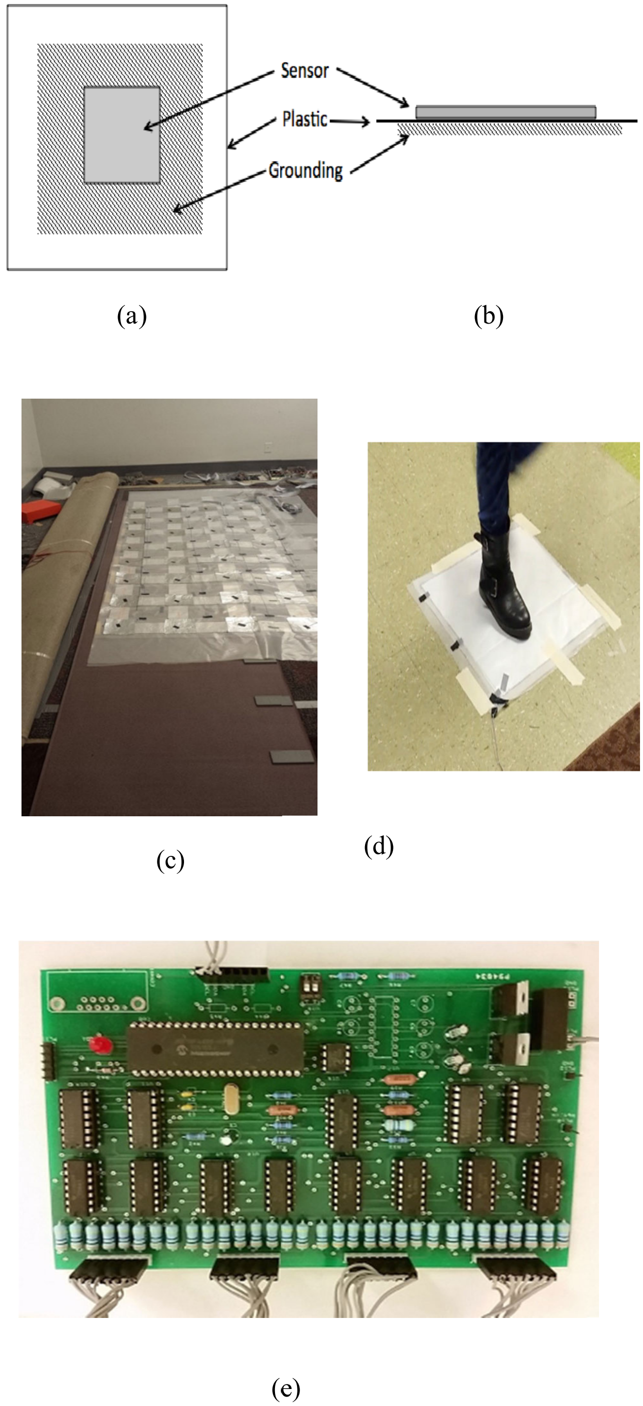

FIGURE 1. (a) the layout of the sensor, (b) vertical cut area of the sensor, (c) one segment of 32 foil sensors, (d) one single sensor(two layer; sensing and ground separated by vinyl), and (e) data acquisition and processing board.

segment of 32 sensors, shown in Figure 1(e). We used the I^2C communication protocol to send and receive data between the boards. I^2C requires assigning one board to be the master and the others to be slaves. Since we have 128 sensors and four boards in our system, each board connects to 32 sensors segment, designated as segments A, B, C, and D. The master is the board connected to segment A and the others are slaves.

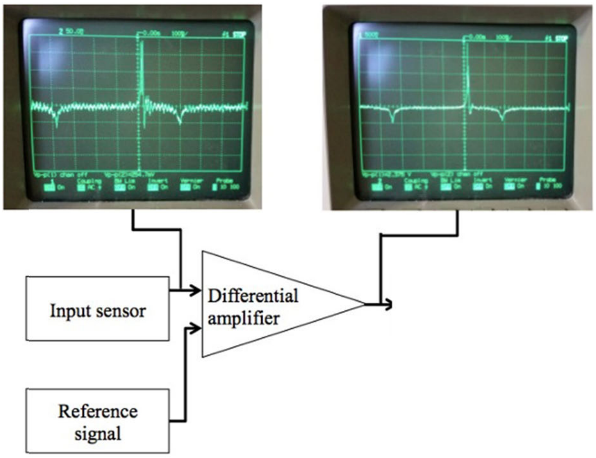

FIGURE 2. The differential amplifier circuit that accepts the scavenged signal (left) and subtracts the 60 Hz noise signal to get the electric signal corresponds to the activity on the sensor(right).

Both master and slaves read the data from their own 32 sensor segment and store it in their local memory. The master board gathers the data first in the system. Once the master has data from all boards, it then sends the data to a computer for further processing and analysis. The same boards used to test and experiment with different carpet segments and features of the carpet; for example, we used all the carpet segments (128 sensors) for Fall detection experiments; two segments to study GAIT analysis see Figure 1(c) above. We used a single sensor to study analog signal characteristics and extract features to identify people (see Figure 1(d). In multiple people (socializing) experiments, we deactivated segment C to provide one consistent path of walk-in same and opposite directions.

As shown in Figure 3, the system consists of the sensors embedded under the carpet, a data acquisition electronic system, and a microcontroller system. The scavenged sensors signals converted into digital values with an experimentally determined threshold using a 10-bit Analog to Digital convertor. An ASCII frame is s result that is sent to the cloud for processing. The software components process the data frames and use different computational intelligence methods to perform the required operations like fall detection, gait estimation, people counting, data visualization, and notification. The smart carpet data acquisition system scans the sensors at N frames/second. We parse the frame data into a binary image that corresponds to the carpet layout. Where '1' means the sensor is activated, and '0' means it is not activated. This image becomes the data structure to perform computations. We conducted different experiments using different people (stunt actors) and layouts depending on the study's functionality.

A. FALL DETECTION

Our smart carpet is used to detect motions and falls. It consisted of four segments, each with 32 sensors. The data acquisition system in Figure 2 scans the sensors and store the data

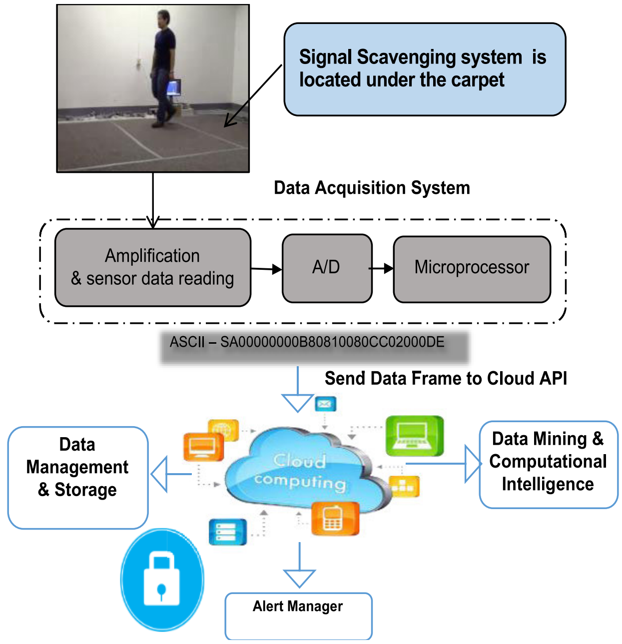

FIGURE 3. System overview: floor-based sensors, data acquisition, analysis, and reporting.

in an ASCII frame sent to the cloud for further analysis and computing. When there is mobility on the carpet, the voltage generated by the sensors that exceed a certain threshold, determined experimentally, is considered active. To study fall detection, ten subjects, each performed eight walk sequences. In each sequence, they performed a fall. The falling patterns adopted from previous work by our eldercare technology research group [3], [45] can be divided into four categories: *falling from standing, falling form tripping, falling from sitting on a chair, and falling from slumping*. Figure 4 shows one walk-tripping-fall backward pattern performed by one of the subjects. The sequence consists of 101 frames, which is equivalent to 14 seconds. Figure 3 below shows the count of the sensors activated once per frame. As shown in the graph, the count is zero at the walk's beginning, with no sensors activation. The moment the subject stepped on the carpet, the sensors activated and counted in each frame. Counts increase or decrease, depending on sensor activation, rate of scan relative to the walk, and noise. So low levels of count occur until a fall occurs, causing a sharp increase in the number of active sensors noticed as seen in frames (71-76).

An ideal scenario for a fall is a jump in the count of active sensors and then a sharp decrease to zero (Frames 92-100). We see that if the fallen walker stays stationary on the ground, the counts are all zero. Figure 5 below shows the walk-fall pattern. Each rectangle represents a set of frames (each frame resulted from one complete scan of the 128 sensors). We sliced the walk into different sizes (window sizes-*WS*) depending on the activated sensors count. Each of these slices represents different time intervals. We studied different time intervals and applied computational intelligence algorithms

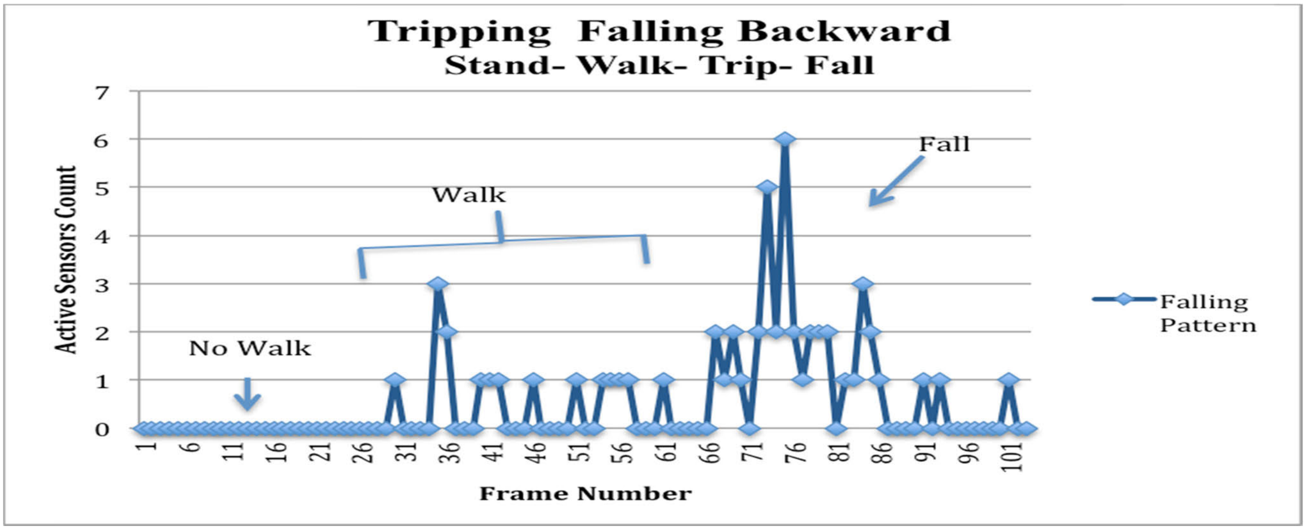

FIGURE 4. Walk-Trip-Fall backward pattern in 14 seconds. The y-axis shows the count of the sensors activated per frame.

to detect the fall. Recorded videos were used as the gold standard to verify the accuracy of the algorithms. We developed and studied three different algorithms; Connected Component Labeling (CCL) [51] with varying sizes of window, the Convex Hull area [53], [7], and a heuristic algorithm based off the count of the activated sensors and their spatial characteristics.

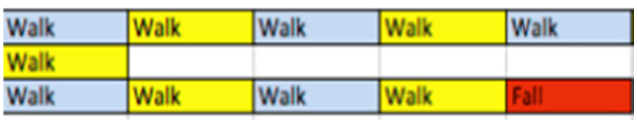

FIGURE 5. Complete walk-Fall pattern. Rectangles represent one frame or multiple ones depending on the window sizes used.

The connected components labeling algorithm classifies the fall when the largest contiguous sub-region size is higher than a predefined threshold determined experimentally. Convex Hull with different window sizes uses the quick convex hull algorithm on the activated sensors' list per frame or group of frames. The area of the polygon resulted from the points forming the convex Hull is computed. To detect a fall, we run the algorithm for different window sizes/sliding windows (WS) and thresholds (TH). Having a constant Threshold with changing sliding window size didn't give a good result. Our approach is to make the threshold variable based on the number of active sensors forming the Hull. The new threshold(TH_{Hull}) is given by equation (1).

$$TH_{Hull} = WS * CS * \alpha_{Hull} \tag{1}$$

WS: the sliding window size,

CS: Convex Size; the number of points forming the convex in a *WS*.

α_{Hull} : constant determined experimentally = 0.3

The heuristic algorithm maps the sensors into a binary image of 128 pixels where '1' represents an activated sensor and '0' otherwise. The count of the neighboring activated sensors computed. Fall determined if the count meets or exceeds some threshold ($TH_{Heuristic}$) given by equation (2).

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

WS: the sliding window size,

$\alpha_{Heuristic}$: constant determined experimentally = 1.2

We conducted the experiments to determine the performance of the different classifiers in detecting falls. Table 1 shows the confusion matrix of all methods and algorithms. The relation between Predicted and Actual classes gives four outcomes. The true positives (TP) and true negatives (TN) are correct classifications. A false positive (FP) and false-negative (FN) is when the outcome is incorrectly predicted. We computed both Sensitivity and Specificity. Sensitivity refers to the proportion of patterns with actual patterns with a fall classified as falls (TP). Specificity refers to the percentage of actual patterns with no fall classified as no fall, 1 – FP.

TABLE 1. Confusion matrix: fall detection.

		Predicted Class	
		Fall	**No fall**
Actual Class	**Fall**	True Positive (TP)	False Negative (FN)
	No Fall	False Positive (FP)	True Negative (TN)

B. GAIT MEASUREMENT

To measure and estimate the gait, we used to modify the system by building two new sensor segments. Each segment consists of 32 sensors. We chose to have moderate resolution square sensors with length 6 inches. The scanning rate was 14 frames/second. We used two segments, each 8 feet long, to match the mat we used the GAITRite system as the gold standard [54]. This system is an electronic walkway used to measure the temporal and spatial parameters by activating its sensors during a walk. Footfall data from the activated sensors are collected by a series of on-board processors and transferred to the computer through a serial port. The gait parameter used in this study: *Ambulation time* defined as the time elapsed between the first contact of one foot and the last footfall. *Step time*: Time elapsed from one foot's first contact to the opposite foot's first contact. The *step length* of the right foot is defined as the distance between the center of the left foot and the right foot's center along the progression line. *Stride time:* Time between successive footfalls of the same foot. The spatial gait parameter of *Stride length* is the distance between consecutive footsteps of the same foot. *Walking speed*: Distance traveled divided by the ambulation time. The subjects walked on the two segments laid on the top of the GAITRite mat. Data is acquired, and gait parameters are extracted and computed.

Multiple subjected asked to walk across the carpet various times (9 subjects with nine walks each) maintaining the same pace. Six walks data dropped due to carpet segment malfunction (the ground plane under sensors disconnected from the board and caused one of the segments sensors to activate simultaneously) during the experiments. To estimate the gait parameters of walking speed, stride time, and stride length, we computed the distance traveled and ambulation time. We determined the number of footfalls using computational and heuristics rules. Deciding a good footfall was our first challenge. We used the active sensor count for a given windows size (sliding window of N active sensors). We choose the threshold experimentally. To compute the walking speed, we calculated the time and the distance between the first contact of one foot and the last contact with the carpet. The time difference is the elapsed /(ambulation) time. Walking speed can be calculated by dividing the distance by the ambulation time. The step time, the time elapsed, divided by the number of steps. Step length is measured by dividing the distance traveled by the number of steps. Similarly, the stride length is computed by doubling the step length. Algorithm-I above shows the procedure to calculate and estimate the gait parameters: Waking speed, stride and step lengths and speeds.

C. SOCIABILITY

o count the plurality of people and measure the sociability of the elderly aging in place, we activated the three segments. We turned off only segment D, as shown in Figure 6. Four volunteers walked across the carpet from A to C or C to A (Longitudinal Direction). The longer traveled distance, the more activated sensors, compared to waking from segment D direction bottom-up (Transverse Direction). We used a binary display of the activated and non-activated sensors on the carpet to see the individuals' traversal, as shown

Algorithm 1 Gait Parameters Extraction

```
N_Frames = 0; // Number of Frames
N_active = 0; // Active sensors
WS; // Sliding window size
FOR each frame F in WS {
   Parse into Binary Image();
   ++ N_Frames
   IF (N_Frames == WS){
      UPDATE (N_active); //Update number of active sensors
      IF (N_active >= TH) // Threshold defined
            experimentllay ++Footfalls
      IF (F == Last Frame){
            TimeElapsed = FinishTime_LF – StartTime_FF;
            DistanceWalked = LastActiveSensorLocation -
            FirstActiveSensorLocation;
            Compute (Number of Steps)
            Compute (Walking Speed )
            Compute (Step time, Stride time, Step length
            stride length )
   }
}
```

Output: Gait Parameters

in Figure 7 below. Each person, individually, performed ten walk trials in traverse direction from the bottom of segment **A** to segment **B** and back to the beginning. Then, multiple persons participated in 2 people, three people, and four people walk trials ten times each. The smart carpet data acquisition system scans the carpets at nine frames per second. Each data frame consists of 128 sensors, where all segment **D** sensors turned off. However, we used them to build a 12 × 12 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 the computation to recognize people on the carpet.

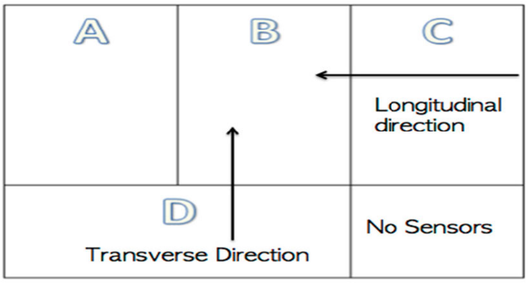

FIGURE 6. Carpet layout: Active segments A, B and C. Sensors in D are turned off. This layout used for all the experiments.

We used Connected Component Labeling (CCL) algorithm. We applied the same procedure for both individual frame and window size of frames encompassing a 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 the

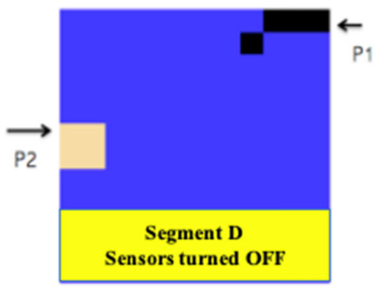

FIGURE 7. Active sensors map: Two people walk in Opposite directions: Longitudinal Direction (A <−> C). All sensors in Segment D turned OFF.

8-connect neighborhood for our experiments to ensure we do not ignore the effect of interference among the sensors, and so we have biased results. Figure 8 shows the carpet layout's binary image for the "*Two People Walking in Opposite Directions*" scenario. It took 4 seconds to perform the walk. At the start of the walk *top image,* the persons were at a separable distance. They were recognized and by their subgroup. However, as shown in the *middle*, they became closer and were not separated. Then when they reached the end of the walk, *bottom*, they were recognized gain.

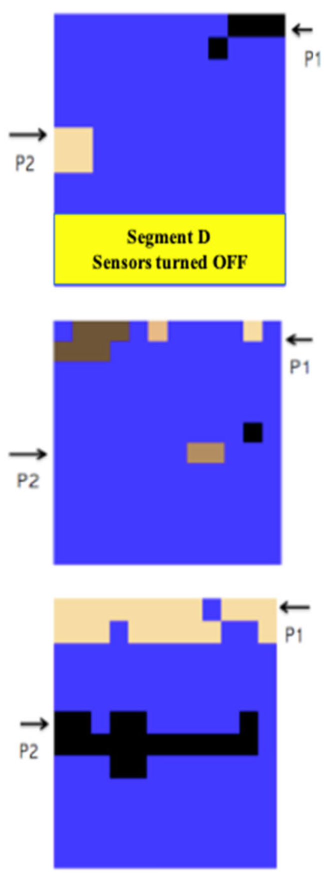

FIGURE 8. Active sensors map: Two people walk in Opposite directions: Longitudinal Direction. frames are grouped in a window of siaze 9 frames/sec (i.e. 1 second ambulation time). Top: Start of the walk, middle: End of the walk, and bottom: the full walk.

We considered the count of the total sensors activated for the full walk, and then divided by the average 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 several people.

D. COOPERATIVE CLOUDLET MODEL

We presented a cooperative cloudlet model. The sensed data processed in the nearest Cloudlet in the mobile cloud computing model, and the results to be sent to the proper users to extract the suitable decision. Several user movement scenarios in the cooperative cloudlet model are shown in Figure 9 [36]. The collaborative cloudlet model consists of several cloudlets covering a specific area where users move within that area. If a user requests certain services, then the nearest Cloudlet will provide the user's requested service if it is available. If the nearest Cloudlet can't provide the service, then the request will be routed to another remote cloudlet to execute the user's request (Figure 9-b). The cooperation process continues until the capable Cloudlet runs the request and sends the results back to the user through the same route.

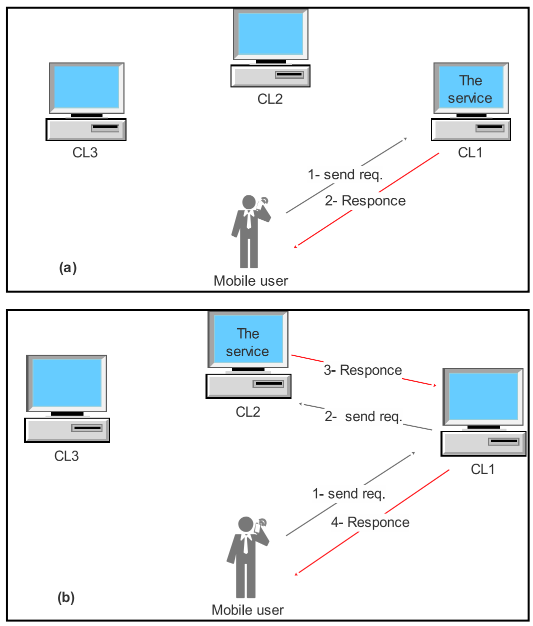

FIGURE 9. Cooperative cloudlet model.

The application of the cooperative cloudlet model in our system implies processing the sensed data, analyzing it, and committing the user's decision. This approach will save time compared to the classical model where the users have to communicate with the primary Enterprise Cloud system, send the sensed data, and wait for the decision [55]. Moreover, this cloudlet model's application becomes more critical, especially in the health-related situation when making decisions in a short time based on collected data is crucial in saving people's lives.

Another important aspect is protecting the data from malicious attaches and unauthorized access during transmission and processing (Confidentiality and Authentication) and incorporating security techniques and encryption algorithms in the intermediate communications between the cloudlet members to secure the data the transmission [56], [57].

III. EXPERIMENTAL RESULTS AND DISCUSSION

Here we discuss the experimental results for different system characteristics and features. The floor-based sensor system is represented by a binary image where "1" is activated, and "0" deactivated sensor. Since the sensor is deactivated (discharged) when stepping off the sensor segment, we can track the person's path and determine the area of walk and fall. Using the Connected Component Labeling algorithm to detect the connected sub-region and based on this sub-region size, we can conclude a fall, non-fall, or a walk. The sub-region size will help eliminate the noise generated from sensors far from the walk /fall path. Similarly, we calculated the convex hull area generated by the activated sensors to distinguish between walk and fall.

We studied both algorithms using different sampling rates. We decide to apply the algorithms at various times that can be represented by the sliding windows (# of frames). We used the recorded video as golden standards, so we determined the constant on both algorithms experimentally—these constants independent of the person's age and traits. We tested the system on ten different people (age, gender, height, and weight). These were all controlled tests in the lab, so we limited the study to ten people. We ran the algorithms to create the data set for the classifiers. We used the recorded video (attached as supporting material) for the real falls. We used Weka framework algorithms such as multilayer perceptron, SVM, and role-based classifier C4.5. Most of them gave close results.

We used the same data representation (binary image of the activated sensors). Different subjects and scenarios help estimate the gait parameters (Nine subjects each perform nine walks) and measure the degree of sociability (Four subjects performed individual walks, in groups of two, three, and four).

A. FALL DETECTION

We studied the performance of the different detection algorithms and their combinations. We used recorded videos as ground truth for our results. Table 2 shows the sensitivity and specificity of the three algorithms and some possible combinations. Connected component labeling algorithm with 10fold cross-validation shows an acceptable result suffered from the true negatives. Convex Hull showed better sensitivity but low specificity. We fused different algorithms; convex Hull and heuristics provided the best results of 95% sensitivity and 85% specificity using WS = 7, $\alpha = 0.3$, and 1.2. Combining the two methods increased the true negatives, but better than any of them individually.

TABLE 2. Fall detection algorithms performance: WS = 7, $\alpha_{Heuristic} = 1.2$, $\alpha_{Hull} = 0.3$.

Algorithm	(Sensitivity)	(Specificity)
Convex Hull Area	90%	80%
Heuristic	86%	80%
Connected Component, Labeling with 10XV	81%	98%
Convex Hull **AND** Heuristic	75 %	89%
Convex Hull **OR** Heuristic	95 %	85%

B. GAIT ANALYSIS

In Gait estimation experiments, we collected 81 walks (75 valid and six invalids). The invalid walks dropped due to malfunction in the carpet. The ground plane got disconnected from the electronics, and the sensors became very sensitive to the noise and activated all sensors in the affected carpet segment. We used collected data from the nine subjects' walks to compute and estimate the gait parameters; walking speed and stride time and length. We compared our results with the readings from the GAITRite system. Figure 10 shows plots of walking speed, stride time, and stride length for each of the walking sequences for both the smart carpet and the GAITRite systems. The walk sequences' estimated walking speed ranged from 66.3 cm/sec to 135.4 cm/sec. Stride length ranged from 41 to 73 cm.

The gait parameters estimated using the smart carpet achieved an excellent agreement with the GAITRite system results. In a few walk trials, we had errors; that is a difference from each system's parameters' average value. For example, for one trial's walking speed, the percentage difference was high, about 10.1%. In that walking sequence, the number of footfalls differed from the number of footfalls measured by the GAITRite; we believe it is due to how our algorithm calculated the number of footfalls. The smart carpet measured time 6.869 seconds, which is bigger than the actual time on the GAITRite 5.96 seconds; the distance traveled on the carpet as measured by the locations of the active sensors was 15.5 foot (472.44 cm) is slightly higher than the one on the GAITRite 14.95 foot (455.8 cm). These differences, we believe, arise from the spatial sampling nature of our devices. In future work, we will build higher resolution carpet segments to identify the footfall more accurately.

We compared the performance of our system with two other systems developed by the Eldercare Technology research group: Kinect [18], web camera [20], and motion capture-Vicon [22]. These systems used GAITRite as ground truth for all validation. The mean percentage difference between the systems and the GAITRite are; 1.34% (smart carpet), 2.9% Kinect, and 0.18%(Web Camera).

C. SOCIABILITY

We performed ten experiments for each scenario: individual, two people (same and opposite directions), Three people

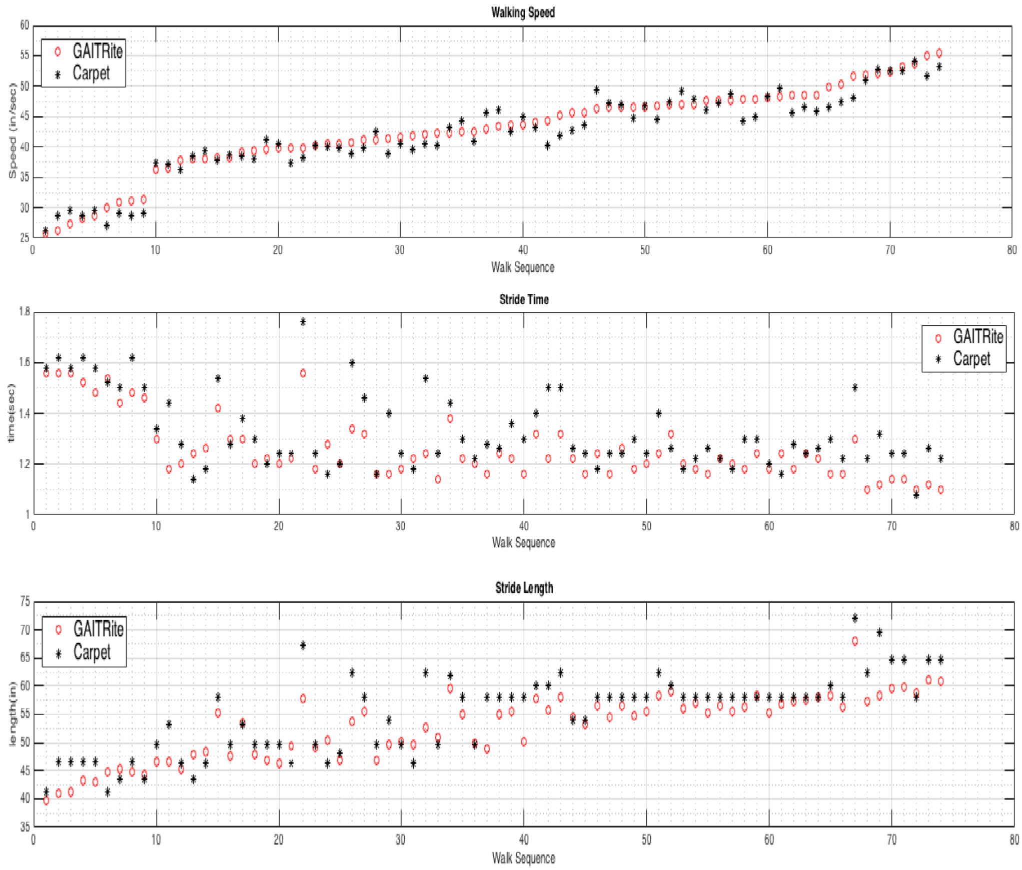

FIGURE 10. Gait parameters for both GAITRite (red circle), and smart carpet (black asterisks); Waking peed, Stride Time, and Stride Length. Nine subjects walk with repetition results comparing walking speed from Smart Carpet and GAITRite systems. Walks sorted in ascending order of speed.

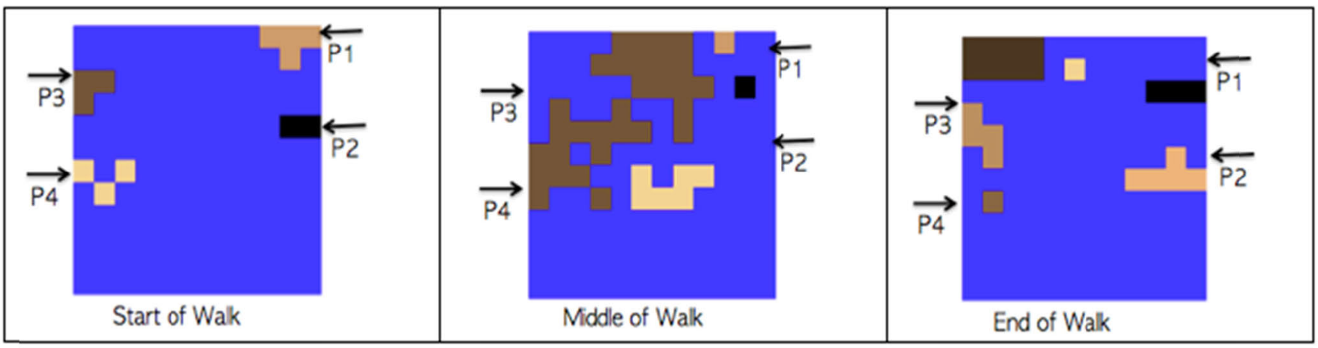

FIGURE 11. Active sensors map: Four people walk in Opposite directions: Longitudinal Direction. frames are grouped *in a window of size* 9 *frames/sec)*. Segment D sensors turned OFF.

(same direction), and four people (equal and opposite detections). In Figure 11, four people walk in opposite directions. At the start of the walk ***left,*** the persons were at a separable distance. They were recognized and by their subgroup. However, as shown in the ***middle***, they became closer and were not separated. Then when they reached the end of the walk, ***right***, they were again separable. 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 ten walk trials. Results showed that we could reliably count the number of people for the "two" and "three" people scenarios. However, when the number of people increased for the same size as the carpet used, it became difficult to count the people reliably (accuracy of 20%). Accuracy is proportional to the number of people walking on the carpet to the carpet size. We could not determine the optimal window size of frames that fit all scenarios, especially when the number of

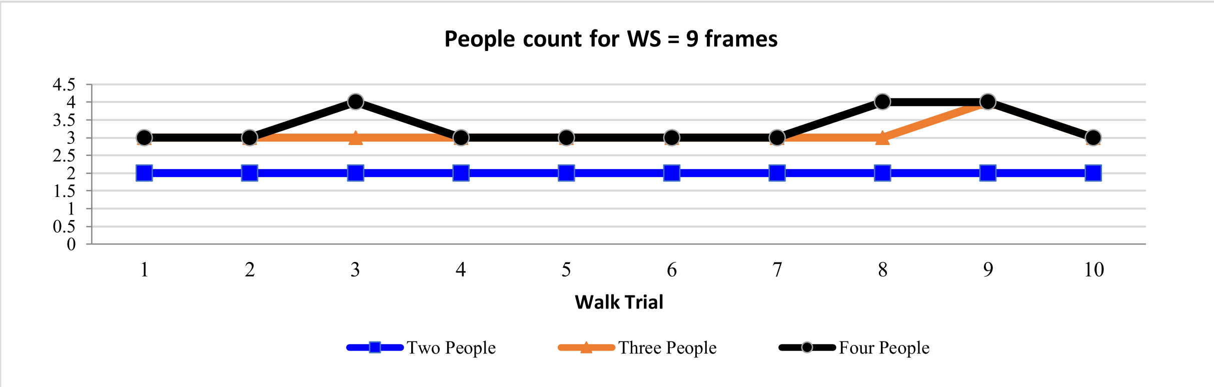

FIGURE 12. People count for ten walk trials average for Windows size of 9 frames for the Two, Three, and Four people walking on the carpet. Segment D sensors turned OFF.

people to the carpet size is big. Figure 10 shows that the count of people for two, three, and four people walking in the same direction at a window size of nine ($WS = 9$ frames, i.e., the algorithm determines the count of people at time intervals one second). As Figure 12 shows that at $WS = 9$ frames, the accuracy of counting people is 100% for two people, 90% for three, and 30% for four people.

TABLE 3. People plurality count using the ration of total activated sensor to the individual walk active sensors count.

Scenario	Activated Sensors (Average)	Activated sensors (individual)	Algorithm result
One Individual	13.62	13.62	1
Two Individuals walk in the same direction	27	14.20	2
Two Individuals walk in the opposite direction	25	14.20	2
Three Individuals walk in the same direction	49	14.10	3
Four Individuals walk in the same direction	58	13.62	4
Four Individuals walk in the opposite direction	72	13.62	4

We evaluated the binary image by counting the '1' pixel value, which corresponds to an active sensor. TABLE 3 shows the average activated sensors count for different scenarios. It is evident that the bigger the area is, the more people walking on the carpet. The count of the active sensors is 72 rounded to the whole number. Comparing this to the 58 for the same amount 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 obtained the count of the plurality of people walking on the carpet by dividing the activated sensors count of the full walk by average of the activated sensors counts produced by a person's walk. The result was rounded to obtain the whole number.

IV. CONCLUSION

Aging in place is possible with the help of a floor-based sensor system. The system unobtrusive, non-wearable, and ensure privacy. Our system is showing a good fit for assistive living. While in the home, it can detect falls with high accuracy, display the data in real-time, and estimate important gait parameters that may help monitor a functional decline; this will help unaffected seniors and those with mild cognitive impairment to live independent lives. When we have multiple people visiting the elderly aging in place, we can determine the degree of sociability by counting the number of guests. As an observer, we can determine if multiple people are walking on the carpet. However, our approach fails when the distance between people tiny compared to the dimension of the sensors we use. In the future, we are considering enhancing fall detection and gait estimation, and scavenged signal analysis in a more fine-grained level. We will be considering higher resolution sensors segments with smaller sensor sizes. With this new design, we can study and develop algorithms to identify the individuals and keep track of their movements. With that in mind, we are considering multi-sensor data fusion. We will build a framework for sensor data fusion and mining this data in real-time. We will create a dynamic, efficient, scalable, and secure runtime of parsing and handling multi-sensor data. How to deal with obstacles such as data imperfections and inconsistencies, misled data association, data fusion portability, machine independence, security vulnerabilities, etc.

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FADI MUHEIDAT (Senior Member, IEEE) received the B.S. degree in electrical and computer engineering from the Jordan University of Science and Technology (JUST), and the Ph.D. degree. He worked for two years as an Assistant Professor with the School of Engineering and Computer Science, University of the Pacific, Stockton, CA, USA. He worked as a Researcher Scientist in an outcome-based research company focusing on data analysis and patient-reported outcomes utilizing predictive modeling tools and algorithms. He is currently an Assistant Professor with the School of Computer Science and Engineering, California State University, San Bernardino, CA, USA. His research interests include eldercare technology, assistive living, the Internet of Things (IoT) architecture, security and communication, sensor and data fusion and processing and real-time decision making, and engineering educations. The advanced use of computational intelligence algorithms, side-by-side with high-performance computing technologies; GPUs, and heterogeneous architecture tools, will help build a complete intelligence and big data-enabled systems. He is also passionate about teaching and adopts different student-centered active learning methodologies in his teaching. He is an ASEE of ACUE, in 2019.

LO'AI A. TAWALBEH (Senior Member, IEEE) received the M.Sc. and Ph.D. degrees (Hons.) in computer engineering from Oregon State University (OSU), Corvallis, OR, USA, in 2002 and 2004, respectively. He is currently an Associate Professor with the Department of Computing and Cybersecurity, Texas A&M University-San Antonio, San Antonio, TX, USA. He is also the Founder and the Director of the Cryptographic Hardware and Information Security (CHiS) Lab (JUST). From 2005 till 2012, he worked as an Adjunct Professor to teach in the Master programs with the New York Institute of Technology (NYIT), DePaul's University, and Princess Sumaya University for Technology (PSUT). He won many research grants and awards. He has more than 90 research publications in many refereed international journals and conferences. His research interests include information security, cryptographic applications, and cryptosystems hardware implementations, mobile cloud security. He is also chairing many international conferences and workshops in mobile cloud security, blockchain, and related cybersecurity areas. He is also a Reviewer and an Associate Editor of many international journals.