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Exploratory analysis of older adults' sedentary behavior in the primary living area using kinect depth data

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Abstract. We describe case studies of clinically significant changes in sedentary behavior of older adults captured with a novel computer vision algorithm for depth data. An unobtrusive Microsoft Kinect sensor continuously recorded older adults' activity in the primary living spaces of TigerPlace apartments. Using the depth data from a period of ten months, we develop a context aware algorithm to detect person-specific postural changes (sit-to-stand and stand-to-sit events) that define sedentary behavior. The robustness of our algorithm was validated over 33,120 minutes of data for 5 residents against manual analysis of raw depth data as the ground truth, with a strong correlation ($r = 0.937$, $p < 0.001$) and mean error of 17 minutes/day. Our findings are highlighted in two case studies of sedentary activity and its relationship to clinical assessments of functional decline. Our findings show strong potential for future research towards a generalizable platform to automatically study sedentary behavior patterns with an in-home activity monitoring system.

Keywords: Activity recognition, depth images, Gerontechnology, Kinect sensor, sit-to-stand analysis

1. Introduction

As the population of people over the age of 65 continues to grow, so does the demand for innovations to promote independence and to support aging in the place of one's own choosing. Advances in health monitoring technologies supplement the health-care providers' ability to identify vulnerable older adults at risk for decline and to deliver timely care and services. Early signs of functional deterioration may be reflected in deviations from daily routine activities [30,46]; hence, selection of sensitive behavioral markers is crucial for the development of successful health-monitoring systems, specifically for early interventions in the case of adverse predictions.

Sedentary activity has the potential to be a behavioral predictor of functional decline. It is defined as "any waking activity with low energy expenditure and a sitting or reclining posture" [32]. As indicated by literature, sitting has deleterious effects on health of

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older adults, increasing the risk of disability [14] and falls [41], leading to medical complications and premature death. Nonetheless, the majority of older adults spend 70 to 80% of their day sitting [32], embedding this behavior in their daily routine. Any deviation from regular sitting activity may signal a change in the older adult's cognitive or physical ability [11].

While the total time spent sitting per day has been the most studied parameter of sedentary behavior, its frequency, variability and temporal patterns may have more subtle associations with the early signs of functional decline [41]. Moreover, the quantity and quality of postural transitions associated with sedentary activity, such as sit-to-stands and stand-to-sits, may be predictive of the older adult's function, mobility and fall risk [14]. The ability to capture multiple parameters of these activities in the free-living environment in the homes of independently living older adults will allow us to reliably monitor changes in sedentary behavior over time and to explore their relationship to clinically significant outcomes, such as falls and functional deterioration.

The aim of this explorative study is (1) to modify existing computer vision algorithms for continuous in-home Microsoft Kinect depth data that detects person-specific postural changes associated with sitting in the primary living area of senior apartments, and (2) to illustrate changes in patterns of sedentary behavior that may indicate preceding functional decline using a clinical case studies approach. Since this is an observational study, the latter is based on the case studies referred to in this manuscript. However, the implications of this study can allow us to test our algorithm in a larger observational study that can then allow us to generalize the outcomes based on a larger participant study. In Section 2 of the paper, we discuss the existing measurements of sedentary behavior, their limitations and our proposed sensor of choice. Section 3 provides details of our system architecture, algorithm assumptions, and subjects for multiple case studies. Algorithm and its validation are presented in Section 4. Section 5 describes the selected case studies of clinical significance. We discuss our work in Section 6 and examine implications for future research in Section 7.

2. Background and related work

Inferring the relationship between sedentary behavior and physical function in older adults requires appropriate measures. A comparatively recent study from behavioral epidemiologist Owen et al. [32] highlights the significance of sedentary time as an indicator of health decline or cardio-biomarkers. The most studied sedentary behavior parameter has been the total time spent sitting per day [14,32,41]. However, frequency, variability and temporal patterns may have more subtle associations with the early signs of functional decline [8]. These parameters may require years of repeated measures to identify baseline sitting "routine" and to track the onset of health deterioration.

Much of the large-scale epidemiological research [1, 14,16,18,40,41] on sedentary behavior has been conducted using wearable sensing modalities such as accelerometers. Accelerometers measure the frequency of lower extremity movement, most commonly at the waist, and a specific threshold for movement counts (usually <100 counts/min with 15 s epochs) defines sedentary activity [8]. However, there is no evidence-based consensus on the sampling rates or cut-off points for these devices, especially for vulnerable older adults with low cardiopulmonary fitness [18]. Moreover, simple accelerometers cannot distinguish between sitting and standing still. Multi-sensor systems, such as combinations of inertial accelerometers, inclinometers and gyroscopes can determine sitting behavior by detecting both movement and posture via change in the angular velocity at the waist [16].

While compliance of wearing these devices has been established as fairly acceptable, the majority of studies have used them for short periods of time (mean $=$ 7 days) [1,14,40]. In addition, several studies reported missing data from lost, misplaced and non-functioning devices [1,18]. Moreover, many of the subjects have been healthy, active, community-dwelling women under the age of 80 [1]. Hence, the assumptions about acceptability and compliance with wearable devices may not be applicable to frailer, older adults in other free-living settings [46]. Hence, wearable sensors are limited in long-term monitoring of sedentary behavior.

While non-wearable sensors are more unobtrusive (i.e. embedded in the environment), their analysis requires more complex, context-aware algorithms. Several studies show promise in detecting heart rate and respiration of a sitting subject with fiber Bragg grating sensor [15], e-cushion [44], and web cam [31]. However, often these systems are tested in tightly controlled laboratory settings with healthy young subjects; thus the feasibility of their application to dynamic, unstructured environments with frail older adults can be contested. A few systems with bed [22] and motion sensors [19] have been tested in realistic settings, such as free-living apartments, but only for a short time periods. Moreover there is a dearth of studies that have related the processed data to clinical outcomes.

We propose to use a single Microsoft Kinect depth sensor to monitor sitting behavior and assess the clinical outcomes on a longitudinal basis. Microsoft Kinect was originally designed to allow controller free game play on the Microsoft Xbox (Microsoft, Redmond, WA). Paired with the gaming console, it can track motion and recognize gestures, faces and voices. In 2011 its Standard Development Kit (SDK) was released to non-commercial developers and since then it has been used in a variety of research settings (Open Kinect; Han, 2013). This low cost and robust device contains a camera, a microphone array, and an infrared (IR) sensitive camera (Fig. 1). The IR camera uses a pattern of actively emitted IR light to create a depth image, where the value of a pixel is dependent on the distance to what it is viewing.

We use the Kinect IR camera output because compared to standard visible sensors its performance remains unaffected under low light conditions which are common in apartment settings. The depth sensor captures only 3D outlines of objects. This privacy-protecting feature is an important consideration for unobtrusiveness in free-living environments. The SDK provides skeletal tracking but it was not used because of its limited range (approximately 1.5 to 4 meters from the device). However, the depth data allows distinguishing between the postural changes of the person to identify sitting as well as other features of the physical environment. In this way, we are able to continuously and unobtrusively monitor in-home sedentary activity of older adults.

3. TigerPlace system and subjects

To establish feasibility of using Kinect to measure long-term changes in sedentary behavior, we expand our work at TigerPlace [4,13,17,34,35,39,43] with a system that monitors older adults' daily activities in their natural living environment. Forty-seven apartments at this aging-in-place community have been monitored unobtrusively for multiple years using a network of motion, radar, depth and bed sensors [35]. Each resident's activity data are supplemented with monthly assessments of function and clinical notes about health changes. Previous work has demonstrated the effectiveness of using our in-home monitoring system to detect early signs of illness using motion sensors [17,34].

Fig. 1. The Microsoft Kinect sensor with the individual sensors labeled.

3.1. System specifications

The aim of using the Microsoft Kinect depth sensor is to monitor activities in the primary living space, including walking, falls [39] and sitting. Since one-bedroom, single occupancy apartments are the most common type of an assisted living residence [46], the primary living space (separate from the bedroom) often includes living room space, dining room space and part of the kitchenette if there is one. Preliminary work showed that older adults spend the majority of their time in this area that can be corroborated by the level of activity captured by motion sensors in other parts of the apartment.

To monitor activities in this part of the apartment, Microsoft Kinect device is positioned with a slight down tilt a few inches below the 9 ft. ceiling on a small shelf above the front door (Fig. 2). Its angular field of view (57° horizontally and 43° vertically), and the extended depth range of 2.3–19.7 ft. covers the majority of the primary living space (168 sq. ft.) in a typical one-bedroom apartment.

3.2. Assumptions and requirements

Our approach to detecting and monitoring sedentary activity relies on the assumption that the majority of it occurs in the primary living space. Often, older adults have a favorite chair in the living space strategically positioned near the window or a TV. This preference of older adults for a "control center" is corroborated by multiple studies in environmental psychology [25,29].

Hence, it is crucial for the proposed algorithm to be *context aware*, or to robustly identify these "control center" chairs in primary living spaces of apartments with varying layouts. Moreover, these have the potential to change over time as the person moves the furniture around. Another requirement for the proposed algorithm to be *person specific*, that is it has to be able

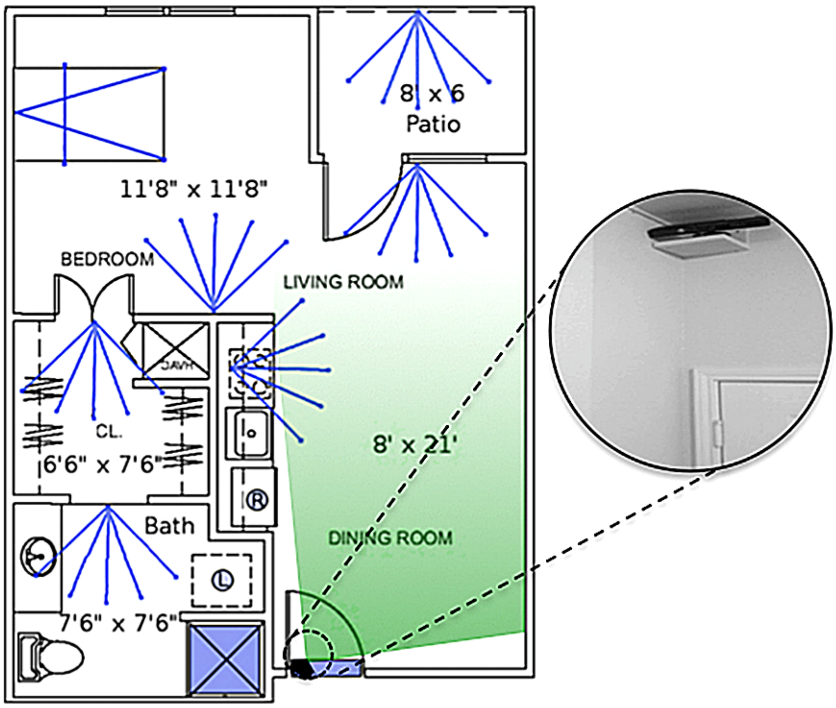


Fig. 2. Floor map of TigerPlace apartment with our in-home monitoring system consisting of motion and bed sensors (blue) and Kinect (black). Kinect is mounted above the main entrance, covering in the main living area (green).

to distinguish between the activity of the resident and that of the visitors (staff or family) or between two residents cohabiting together.

3.3. Subjects

To achieve our study's aim of linking long-term changes in sedentary activity to health events, we followed the ***multiple case study*** methodology to investigate clinical outcomes across residents with different health conditions [45]. This design allows an in-depth detailed exploration of trends in the behavioral events using a small number of subjects. We chose five TigerPlace residents with varying levels of physical activity for this exploratory study of long-term changes in sedentary activity as related to health events. The subjects are diverse but overall representative of older adults that reside in assisted living facilities [35], in terms of age, gender and functional abilities. Our sample consists of three residents living alone and one married couple. It is important to note that only 6–13% of assisted living residents are couples [9,24] while the majority of residents live in single occupant apartments [24].

Our sample was on average 92 years old, 100% Caucasian, and 60% female. The residents have varying functional abilities, such as mobility status, number of co-morbidities and medications and level of care needed (Table 1). These are important factors to consider in understanding changes in sedentary behavior. Old age is associated with reduced physical activity, so one may expect more time to be spent in the apartment sitting. Men and women may have different lifestyle preferences and routines that affect their sitting. Use of assistive devices (such as a cane or a walker) during ambulation is an important consideration because it also affects postural changes as the person gets up or sits down. Various medical conditions prevalent in older age, such as musculoskeletal and cardiovascular problems, affect fitness and physical abilities; those with a higher burden of disease (higher number of di-

Table 1

Resident characteristics

Resident	1*	2*	3	4	5
Gender	Male	Female	Female	Male	Male
Age	98	91	88	99	88
Ambulation	Self	Walker	Self	Walker	Self
# Diagnoses	4	5	4	15	21
Medications	10	10	19	18	22

Note: *Residents 1 and 2 are a couple and live together.

agnoses and medications) are more likely to be sedentary. Moreover, these residents have varying furniture layouts to demonstrate the feasibility and generalizability of using Kinect in unstructured, dynamic settings.

We chose to analyze data from a ten-month period because this time frame is long enough for functional changes and adverse health events (e.g. falls, depressive symptoms) to occur. In Section 5 we describe two case studies of observed changes in sedentary routines preceding adverse health events, as well as their relationship to clinical screening tests.

4. Computing sitting from depth data

Our algorithm identifies postural changes (stand-to-sit and sit-to-stand) in the context of the sitting areas (Fig. 2). While Kinect has a skeletal tracking SDK to identify standing and sitting [28], it requires the person to be facing the sensor within a narrow depth range, which is limiting in a natural living environment where dynamic changes can occur in the course of the daily living activities of a person. Further, we describe our algorithm and validate the results against manually extracted “ground truth”.

4.1. Data filtering

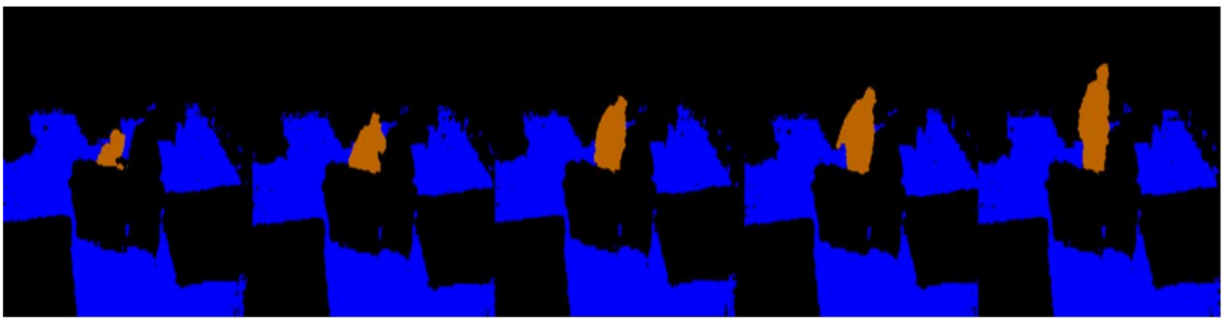
Our continuous real-time data capture system stores the raw depth data. A dynamic background subtraction algorithm identifies foreground pixels from the depth imagery of the Kinect using mixture of Gaussians approach [39]. For every movement detected in the apartment, a motion file is generated with 3D information of the moving object: *height* of the moving person, *x and y location* i.e. the location of the centroid of the moving person in the X and Y plane with respect to the sensor, and the *time stamp*. This information and the depth data are used to compute sit-to-stand and stand-to-sit events.

The depth data from the Kinect sensor can be noisy because IR light scatters when it hits objects. To handle this, we filter the height signal with the Savitsky-Golay filter [37] that uses a least squares fit convolution for smoothing the signal. An example of the extracted foreground for a sit-to-stand event is shown in Fig. 3.

4.2. Occlusion detection

The next step in our approach is occlusion detection. One of the major obstacles in dynamic activity monitoring has been occlusion detection. Occlusion is the obstruction of persons or objects from the sensor’s field of view. This could be caused due to multiple reasons such as objects blocking person from the sensor’s field of view or due to a person entering or leaving the field of view so part of the body is hidden from the sensor. Since our algorithm uses data from actual apartments, the scene is constantly changing: objects such as furniture are constantly getting moved around; people are constantly moving around; and visitors like housekeeping staff enter the apartment. This dynamic environment creates a strong need to be able to detect the presence of occlusion so that the relevant sequences can identified and further processed to gain more information about the environment.

Several studies have tried to address this issue. In [36], Rougier et al. used depth sensors to detect falls. They addressed the problem of occlusion by identifying occlusion as the complete disappearance of the sil-



(a) (b) (c) (d) (e)

Fig. 3. Example of a sit-to-stand event. The resident in the armchair is identified as the orange foreground against the blue ground plane (discussed in Section 3.1) and the static black background. The height of the resident’s outline increases as he gets up, from (a) till he is completely upright (e). The lower part of the person is occluded as he gets up because the armchair is facing away from Kinect.

houette from the field of view. In [23], Hinterstoisser et al. tried to address occlusion by extracting the silhouette of a given object by ignoring the pixels whose depth value exceeds a certain threshold value.

However, both these techniques have disadvantages that need to be addressed. For example, in [36], the authors detect complete occlusion. However, it would be extremely useful to detect partial occlusion since many activities involve partial occlusion; especially in a dynamic environment. Similarly, the algorithm described in [23] addresses occlusion by an approach similar to the bilateral filtering approach described in [42] but some pixel information gets lost in this approach that may be useful to activity detection.

In order to address this, we utilize the method used in one of our earlier work [3]. In that study, we used a fuzzy inference based system approach to compute the degree of occlusion using silhouette information. The features include information such as bounding box parameters (height and width of the minimum sized bounding box that completely surround the silhouette), and silhouette pixel distribution features (horizontal and vertical projection information) that provide more information about occlusion. The details for the fuzzy rules are provided in [3]. The output from the fuzzy inference system is the occlusion confidence or degree of occlusion. This is a value between 0 and 1 with the value 1 representing that the silhouette is completely occluded and 0 representing that there is no occlusion present.

Figure 4 provides an example of the different degrees of occlusion color coded so that the darkest color represents the least occlusion and the lightest color represent the highest occlusion. In this particular example, Fig. 4(a) has an occlusion confidence of 0.1 and Fig. 4(c) has an occlusion confidence of 0.8.

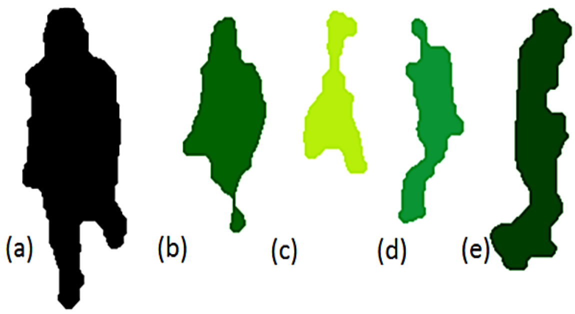


Fig. 4. Sample silhouettes color-coded to represent different occlusion confidence values. The darker color represents lower degree of occlusion of (Fig. 4(a) and (e)) and the lighter colors represent a larger degree of occlusion with Fig. 4(c) having the highest confidence value.

Once we obtain the degree of occlusion based on this method, we learn the sit locations by identifying the regions where there is maximum change in height of a moving person. These locations are updated dynamically to account for scene changes, such as moved furniture. In case of multiple residents we differentiate the sit locations computed in Algorithm 1 using fuzzy *c* means clustering [5].

4.3. Stand-to-sit detection

Algorithm 1 describes our method to detect stand-to-sit events in dynamic environments using features collected from the depth data. Before we extract the activity patterns for the residents, we first "learn" their sitting locations based on past behavior. We do this by detecting the sitting locations of the people by computing the minimum and maximum height of the people for each location in the field of view. The locations that have the highest change in the height values are the identified sitting locations. Once we compute the locations, our next step is to go deeper into the activities taking place in the room. Using the foreground information we extract from the continuous depth data collected, we examine the foreground features to compute activities associated with the sedentary behavior patterns of the residents. From our empirical analysis on data collected in laboratory settings, we observed that when the person sits on a chair or a couch, the foreground gets smaller and smaller as the depth values of the person get closer to that of the stationary chair or couch and blend with the background. This leads to increase in the occlusion confidence of the activity over time. Using this increase in occlusion confidence over time, we can successfully extract the sit-to-stand and stand-to-sit events. This feature is important to consider in a dynamic environment since it helps to distinguish between other activities, such as bending over the chair or picking something from the floor. In these activities, there is lesser temporal change in the occlusion confidence that helps filter out these events and improve the accuracy of our algorithm.

4.4. Sit-to-stand event detection

The detection of sit-to-stand events is different from the stand-to-sit ones. The motion files contain the information only when movement is above a certain threshold. However, during the beginning of a sit-to-

Algorithm 1 Stand-to-sit measurement algorithm

```
/* Initialization: Learning Prior Locations */
Get the motion files recorded in the room for one week

For day = 1 to 7 do
    Compute the max, min height stored at each
    location
End For

Find the locations with the maximum change in height. Cluster the locations to find sitting locations. Remove
locations that have hits less than three per week.

/* Computing Stand-to-Sit */
For day = 1 to nDays
  For path = 1 to nPaths

    If there is any change detected in the background,
      recompute sitting locations.
    End If
Obtain the height of the moving object as ht,
    Obtain maximum height as maxHt
    Compute the least distance dist to the sit locations

    If dist > distThresh Or minHt > (maxHt − 20) then
      continue
    End If

    Filter ht using Savitsky-Golay filter
    Obtain x-y locations for path file as xLoc, yLoc
    Compute temporal difference as dXYloc, dHt
    Find times t1 where – (dHt) > htThresh
    Find times t2 where dXYLoc > horzThresh
    Compute intersecting times between t1 & t2 at t12
    Compute the occlusion confidence as occConf
    Compute temporal difference as dOccConf

    If dOccConf over t12 > 0
      Detected Stand-to-Sit
    End If

  End For
End For
```

stand event no motion file is saved because the person is initially stationary and there is no foreground information. Thus, we use raw depth data to get accurate information about the context. To compute this upward motion, we use the *optical flow* method.

4.4.1. Computing optical flow

Our method to detect sit-to-stand is described in Algorithm 2. We implement an optical flow technique described in [7] to detect large movements in the field of view. It combines the local neighborhood information of each pixel in the image along with the global features of the image to extract motion information of the objects present in the sensor's field of view [7].

The advantage of using the combination of local and global image features is that it is robust to Gaussian noise while still being able to detect dense optical

Algorithm 2 Sit-to-stand measurement algorithm

```
/* Initialization: Learning Prior Locations */
Get the motion files recorded in the room for one week

For day = 1 to 7 do
    Compute the max, min height stored at each
    location
End For
```

Find the locations with the maximum change in height. Cluster the locations to find **sitting locations**. Remove locations that have hits less than three per week.

```
/* Computing Sit-to-Stand */
Load motion files and sit locations extracted
For day = 1 to nDays

  For path = 1 to nPaths
    If there is any change detected in the background,
      recompute sitting locations.
    End If

    Obtain the parameters ht, maxHt, minHt, dist

    If dist > distThresh Or minHt > (maxHt − 20) then
      continue
    End If

    Filter ht using Savitsky-Golay filter
    Obtain x-y locations for path file as xLoc, yLoc
    Compute temporal difference as dXYloc, dHt
    Find times t1 where dHt > htThresh
    Find times t2 where dXYLoc > horzThresh
    Compute intersecting times between t1 & t2 at t12
    Compute the occlusion confidence as occConf,
    Compute temporal difference as dOccConf

    If dOccConf over t12 < 0
      Obtain tEvent as the first time frame from t12
      Extract videos starting from 2 seconds prior to
      tEvent as tStart and ending at 2 seconds after
      tEvent as tEnd
      Run optical flow algorithm on the extracted
      bounding box from tStart to tEnd
      Find the number of frames with a positive upward
      velocity as noUpFrames

      If noUpFrames > 0
        /* Detected Sit-to-Stand event
      End If
    End If
  End For
End For
```

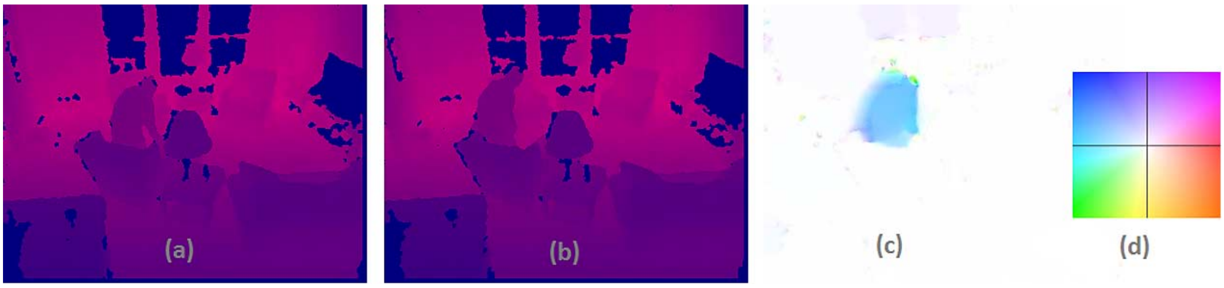


Fig. 5. Sample depth images (pseudo-colored) of a TigerPlace resident getting up ((a) and (b)). The optical flow motion is shown in (c) with the color coding format as shown in (d). As can be seen in Fig. 4(c), there is an upward motion that is detected using the optical flow method which captures the sit-to-stand transition of the person as she gets up from the recliner.

flow fields i.e. concentrated regions with movement in the same direction. Using this method, we can detect an upward motion corresponding with the sit-to-stand event. Figure 5 shows an example of the optical flow method output for a sit-to-stand event. Here, images frames (Fig. 5(a) and (b)) represent the depth images of a resident getting up from a recliner in an apartment at TigerPlace. These images are pseudo-colored for visualization. Figure 5(c) shows the results after using optical flow. Figure 5(d) shows the Waterbury color coding scheme [2] to show the direction of motion. As can be seen in Fig. 5(c), the movement is in the upward direction (upward-left to be exact). Hence, this frame represents a person moving up and gets detected as one of the frames with upward velocity. This is then used by the algorithm (Algorithm 2) to calculate the *noUpFrames*. This is then used to detect the sit-to-stand events.

We use the occlusion confidence to detect the postural change, where a positive value indicates the resident getting up from a chair. This is the reverse of the stand-to-sit pattern so instead of an increase in the occlusion confidence measure, we see a corresponding decrease for a sit-to-stand event. Moreover, to increase the speed of the optical flow algorithm, we compute the bounding box of movement for every frame in a given depth sequence and compute the optical flow for the pixels only within that bounding box area. This significantly reduces the frame size and significantly improves processing speed that is important for a continuous monitoring algorithm.

Using these algorithms, we can successfully detect sit-to-stand as well as stand-to-sit activity events as well as the time and the location where these transitions take place. Once we detect these events, we can then compute the sedentary sitting time by taking the time difference between the stand-to-sit and the corresponding sit-to-stand event to measure the time the person was sitting during one sit activity event.

Table 2

Validation results of the hybrid sitting time algorithm (STSALGO) (mean hrs/day)

Resident #	STSALGO time	Ground truth	Diff. time
1	8.73	9.07	0.34
2	5.78	6.38	0.60
3	7.48	7.44	0.04
4	11.70	11.18	0.52
5	10.63	10.26	0.37
Average	7.95	8.21	0.27

4.5. *Algorithm validation*

The algorithms yield the timestamp of each detected posture change for each individual in a given time period. We define a *period of sitting* as the time difference between a stand-to-sit posture change and the next sit-to-stand from the chair. To validate the accuracy of the measured sitting times two independent researchers observed raw depth videos and manually recorded times of posture changes as “ground truth”.

Three methods were implemented on pilot data from five TigerPlace residents. A total of 23 observation days, i.e. approximately 33,120 minutes of depth videos (average 4 days/resident), were selected for the manual validation (Table 2). We sampled a variety of week days, weekends and holidays to account for variation in habitual sitting activities. Day to day variability in sedentary behavior was affected by these temporal factors; hence we decided to aggregate the data into larger time periods, such as weeks or months when examining long-term trends. The three methods include (i) the rule based system to detect both the sit-to-stand, as well as the stand-to-sit events (STSRB), (ii) the hy-

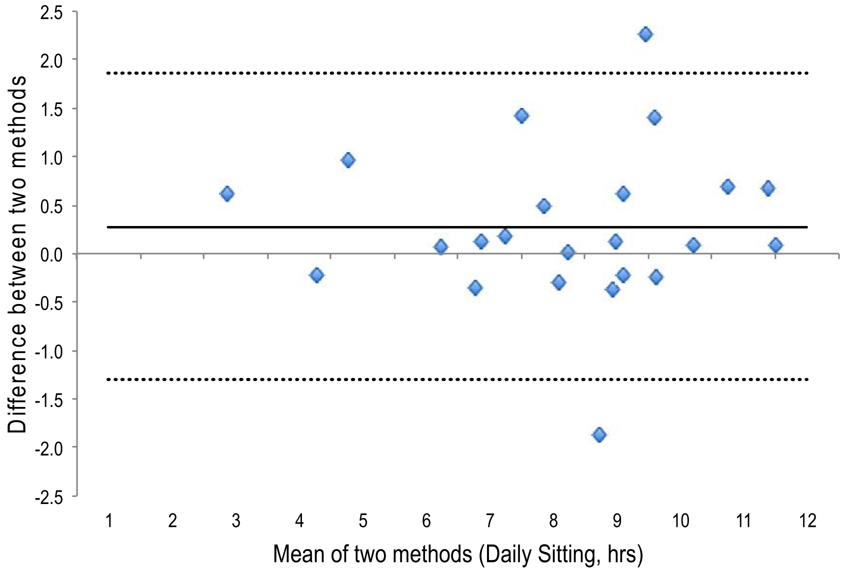


Fig. 6. Bland Altman plot for Kinect algorithm versus manually extracted "ground truth". Each blue point is a 24-hour observation. (Solid black = mean difference, dotted black = 95% CI).

brid method that involves using optical flow to detect sit-to-stand events, and the rule based method for the stand-to-sit events (STSALGO), and (iii) the optical flow method for detecting both sit-to-stand, as well as stand-to-sit events (STSOF).

We found a strong correlation between the manual extraction and the algorithm for daily sitting time (STSALGO $r_{(23)} = 0.934$, $p < 0.001$). The mean error across all observations was 17 minutes per day. The Bland Altman Plot (Fig. 6) depicts the difference between the measurements by the two methods for each observation against their means [6]. All but two observations fall within the 95% confidence interval, showing agreement between the "ground truth" and our algorithm. The major source of the error stems from a few untypical days with multiple visitors; however our assumption is that these rare cases do not affect the general daily routine of sedentary activity.

Table 3 gives the comparison of the STSALGO with other two methods: STSOF, and STSRB. With 21 degrees of freedom (23–2), all three methods are highly significant at $p < 0.01$ with respect to the ground truth values. Using the Intel quad core i5 3470 processor, the computation times to compute the sitting times for the ten month period per resident was approximately equal to 62 hours (STSRB), 75 hours (STSALGO), and 145 hours (STSOF). The average computation time per resident per day is given in Table 3.

An interesting finding while comparison between the three methods was that all three were significantly correlated with the ground truth at an alpha level of 0.95 for statistical significance. That said, if the acceptable accuracy was greater than or equal to 0.9, then the acceptable algorithms will be STSALGO and STSOF. However, if there were computation restrictions, then STSALGO and STSRB may be the more viable options. The other point to note here is that the average computation time for the STSOF is significantly higher than the remaining counterparts because there are more instances of potential stand-to-sit activities (including false alarms like bending or detected height changes due to the dynamic environment) that increase the number of times the optical flow method executes which causes the increase in computation time.

Table 3

Validation results for the three methods using the pearson's correlation and the computation times (mean hrs/day)

Resident #	STSRB SSE	STSOF SSE	STSALGO SSE
1	0.13	0.1058	0.1156
2	0.41	0.358	0.36
3	0.041	0.01	0.0016
4	0.28	0.121	0.2704
5	0.15	0.116	0.1369
Pearson's correlation	0.89	0.945	0.934
Computation time (per day in mins)	12.38	28.11	15.41

These computation times are measured using the Parallel Computing Toolbox available with Matlab programming using the local computer. If more resources are available, the algorithms can work much faster with distributed computing spread across multiple computers.

Overall, our algorithms were able to identify and track sitting locations of multiple residents with different apartment and furniture layouts. Moreover, it adapted to person-specific abilities. For example, an older adult with an assistive device (Residents 2 and 4) has a different sequence of postural changes associated with a sit-to-stand event than a resident without one. Our algorithm adjusted to handle occlusion generated by the walker positioned in front of the chair as well as the orientation of the chair with respect to the Kinect sensor.

5. Clinical case studies

Our algorithm was able to reliably detect routine sedentary behavior of older adults in their natural living environment. To illustrate how this data can be used clinically, we explore longitudinal changes in sitting activity in the context of known health events.

We employ a retrospective multiple case study design that allows a detailed exploration of trends in the behavioral events [45].

In accordance with the University of Missouri Institutional Review Board for human subject protection, all personal data was de-identified. Our outcome of interest is the daily sitting time, or the total duration of all periods of sitting per day. It is aggregated either per week (Case Study 1) or per month (Case Study 2) with a corresponding mean and standard deviation.

We focused on two different timeframes to show possible pattern changes preceding adverse health events (e.g. falls). We also used monthly clinical assessments extracted from the electronic health records (EHR). Timed Up and Go (TUG) test performed by licensed TigerPlace clinicians served as the predictor of each resident's function. TUG measures the time it takes for a person to get up from a chair, walk 10 ft., turn around, walk back to the chair, and finally sit down. Increase in TUG time is correlated with increase in fall risk [33]. Hence, we hypothesize that as the resident's TUG score decreases they will be more sedentary.

5.1. *Overall findings*

We found that for our subjects the sitting time in the living area ranged between 6–11 hours (35–64% of the waking time). This indicates that sitting in the living area is a large part of the resident's daily routine. Hence, studying changes in this behavior over an extended time period can provide insights to predicting health decline of frail older adults. We present case studies of these changes for (1) a single resident, and (2) a couple inhabiting the same apartment.

5.2. *Case study 1: Single resident*

We present a case study of an 88-year-old female TigerPlace resident (Resident 3) and explore trends in her sedentary behaviors from October 2012 to January 2013. During this time period she experienced a number of health changes recorded by a clinician in her EHR. Overall this resident has multiple chronic conditions that include hypertension and vision problems. She is independent in activities of daily living and ambulates without assistive devices. However, she needs help with more complex activities, such as managing her medications, finances and cooking.

From the data collected with the Kinect, we noticed that the resident likes to sit in multiple locations (chairs and the sofa), which were identified by the algorithm as "control centers". Over the period of 122 days we captured 2,779 sitting episodes that lasted between 5 and 25 minutes (mean $= 11 \pm 3$). On average, the resident had 22 episodes of sitting per day (range = 5–54), which amounted to 4.91 hours (range = 0.86–9.81) of daily sedentary behavior in the primary living area. The number of sitting periods positively correlated ($r_{(122)} = 0.779$, $p < 0.001$) with the total sitting time per day.

In establishing trends over time we decided to focus on weekly rather than daily averages. High day-to-day variability may be an artifact of a particular weekly schedule [11], but a weekly mean may be more sensitive towards the slow onset of functional changes. Figure 7 depicts the hours of daily sitting (blue line with dotted error bars) and the number of daily sitting periods (grey columns with solid error bars) aggregated per calendar week for the duration of four months.

Overlaid in red are the clinical notes extracted from the EHR. During the month of December 2012 the resident complained of depressive symptoms (red box). On January 8, 2013 she fell in her bedroom at night (red star). Later in the month she complained of mi-

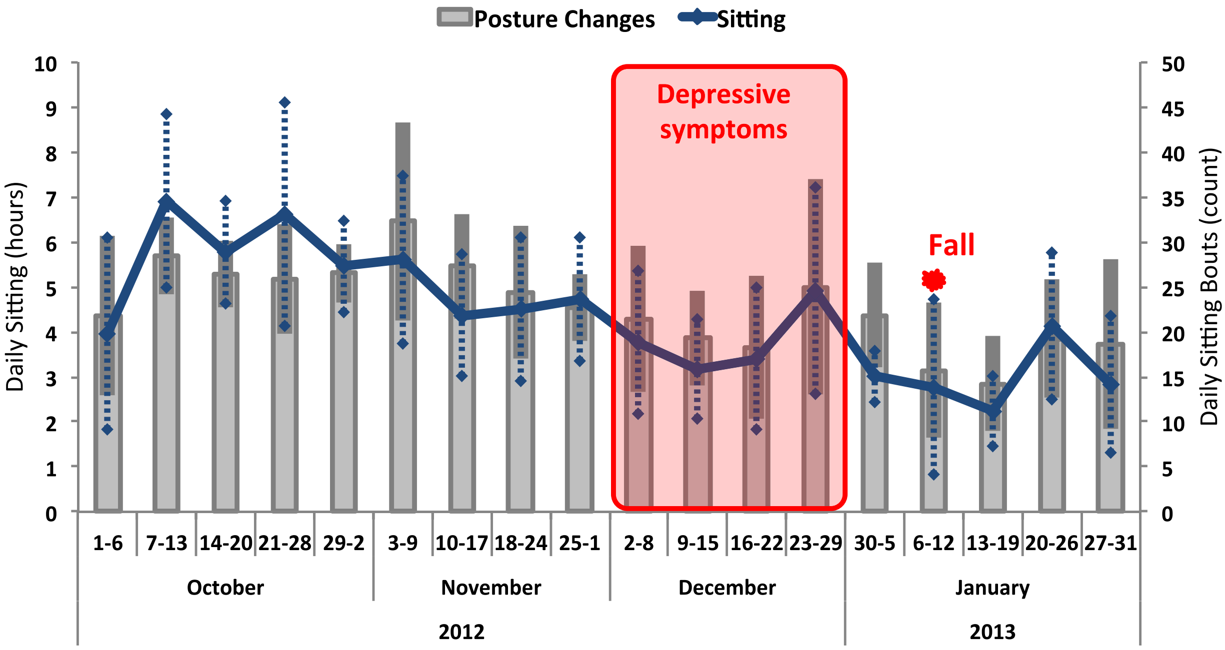


Fig. 7. Graph of Daily Sitting (left Y-axis, hours) and Daily Sitting Periods (right Y-axis, frequency count) averaged by week over a period of four months from October 2012 to January 2013 for the single resident. The daily sitting duration is indicated by blue line with dotted error bars and the number of daily sitting periods by the grey columns with solid error bars. The red dot over January 2013 indicates a fall reported by the resident.

graine headaches, which prompted her to visit emergency room (ER) on February 5, 2013 (not shown).

We included October and November activity as "baseline" behavior because there were no complaints recorded in the EHR. The monthly mean for October is 6 hour of daily sitting with high week-to-week variability, but in November on average the resident was sitting less, at 4.8 hours/day. This number decreased even more in December to an average of 3.7 hours of sitting/day. The trend is non-linear with a spike in activity during the holiday week of December 23–29. Regardless, this decline in sedentary behaviors continued into January, with an average of 3.1 hours/day in the week prior to the fall.

A change in such routine behavior may be driven by poor health. It coincides with the appearance of depressive symptoms and precedes a fall incident. This hypothesis is supported by clinical assessments from the EHR that also show a decline in function during this time period. TUG time increased from 11.32 s (within normal range for this age group) in November to 13.87 s (close to 14 s cutoff for fall risk) [33] in February.

Decreasing sedentary activity in the primary living area may be explained by the resident's decision to spend more time in the bedroom due to poor health. This observation is corroborated by the data collected with passive infrared motion sensors in the bedroom. These sensors are placed in each room of the TigerPlace apartment (Fig. 2); in the bedroom it is mounted on the wall near the bedroom door [21,38]. There is change in the activity detected from the motion density maps, which corroborates with our detected change in routine sitting behavior.

5.3. *Case study 2: Couple*

The second case study illustrates our algorithm's approach to differentiate between multiple people inhabiting the same living space based on their favorite sitting location. Note that in the two resident case, we distinguished between the sit locations using the fuzzy c means clustering technique with the number of residents equal to the number of clusters. The advantage of using fuzzy clustering is that it gives the best result in the case of overlapping datasets [5]. This is useful for both conditions: when there is noise in the depth data information, as well as if the sitting locations can vary, such as a couch so there is a degree of uncertainty associated with the locations. It should be noted here that we empirically tested the performance of both k means and fuzzy c means for this case study for a period of four weeks (randomly selected days) and found the fuzzy *c* means algorithm to better identify the sit location clusters. For our validation study, the algorithm was accurately able to associate one cluster with the particular resident without error. However, it should be noted that this couple has a very sedentary lifestyle which further inhibits changes in their behavior patterns.

We explore sedentary activity of a married couple that shares a one-bedroom apartment during 10 months, from January to October 2013. Resident 2 is a 91-year-old female who has a number of typical chronic conditions that include hypertension, diabetes and urinary incontinence. Resident 1 is 98-year-old male with fewer diagnoses but over time his health declined. He experienced a fall on January 7 and again on May 21 2013, which prompted a trip to the ER.

In the previous case study we aggregated daily sitting activity by week, but here we chose to show a long-term trend. We calculated mean and variance of the daily total time spent sitting by month. Moreover, we examined the relationship between the resident's sedentary activity and monthly clinical assessment of function, TUG time.

Each resident's individual trend in sedentary activity (red line – female; blue line – male) and the two falls experienced by the male (blue dots) are presented in Fig. 8. We observe that the female resident has a more stable trajectory of sedentary behavior. Throughout the 10-month period she spends on average 7.47 hours sitting in the living room during the day (SD = 0.73, range = 6.7–8.84). Her day-to-day variability during the each month (designated by solid red error bars on each time point) has a mean of 3.1 hours (SD = 0.55).

Meanwhile, the male resident shows a trend of declining sedentary activity in the living room. In January he sits on average 10.53 hours/day while in October his daily sitting decreases to 5 hours/day. The overall mean for 10 months is 6.6 hours while the variability is 2.04 hours, which is 2.7 times greater than his spouse's. His average day-to-day variability is also higher (dotted blue error bars), at 3.7 ± 0.83 hours. For the female resident, a fitted linear line has a slope of −0.042, reflecting a stable trajectory, while for the male resident the slope is −0.661.

This sharp decline in sitting is punctuated by two falls the male resident experienced in January and May. The female resident did not report any negative health events during this time. Moreover, the male resident's sedentary activity detected by our algorithm correlates with clinical assessment of function. In Fig. 9, daily sitting time negatively correlates with TUG time ($r_{(7)} = -0.886$, $p < 0.05$). As time spent sitting decreases, the time it takes to get up from a chair and walk 10 ft. increases. Over the 10 months, TUG time increases 50%, from 21.34 s in January to 31.00 s in July. This relationship does not hold for the female res-

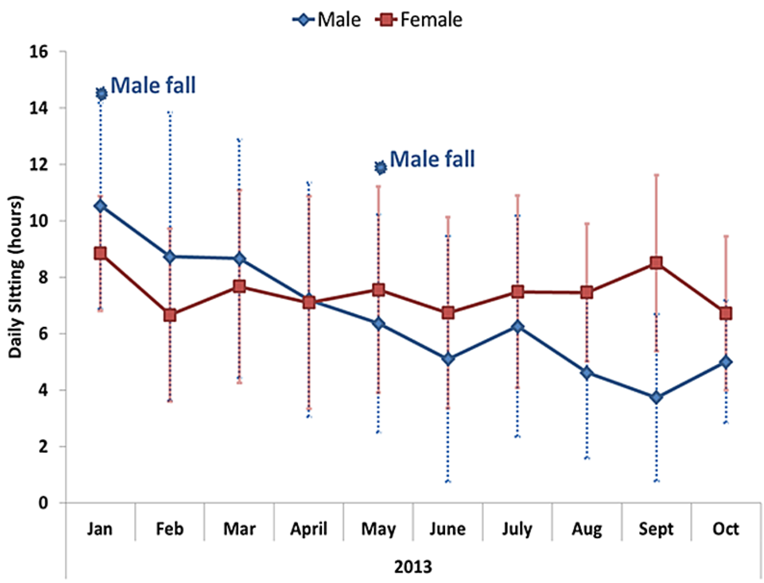


Fig. 8. Graph showing Daily Sitting mean and standard deviation in hours, aggregated by month, from January to October 2013 for two residents (red line – female, blue – male). Blue dots are labeled as months when the male resident reported a fall (01/07/2013 and 05/21/2013).

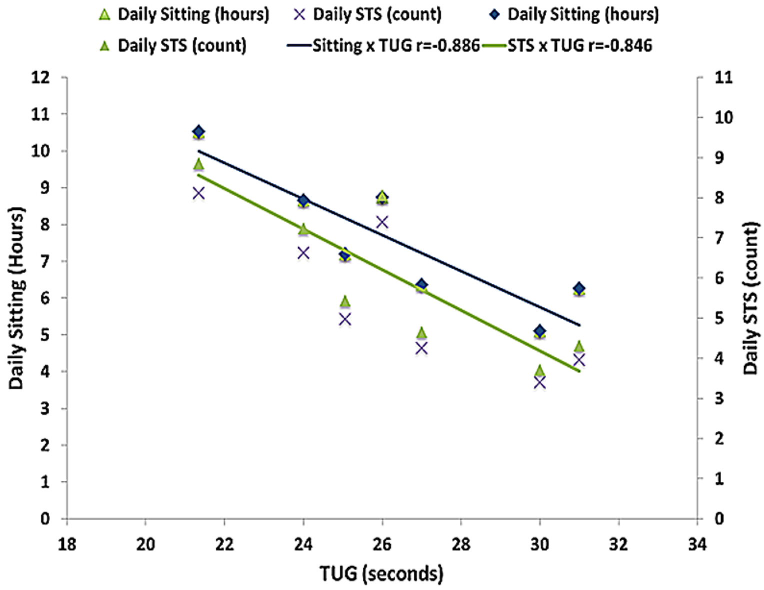


Fig. 9. Graph of monthly average Daily Sitting (left y-axis, hours) and daily STS (right y-axis, frequency count) with monthly TUG clinical assessment (x-axis, s) for the male resident from January to October 2013.

ident ($r_{(5)} = -0.194$, n.s.). Her TUG time fluctuates from month to month within the range of 26–30 s.

6. Discussion

The two case studies illustrate differing trends of sedentary behavior changes that precede adverse health events. While, in general, increased sedentary activity is associated with poor function in older adults [14,41], we found that deviations from the daily sedentary routine (an increase or a decrease in average sitting time, as well as its variability) may be associated with acute events, such as falls. We found a negative association between frequency and duration of sitting and the clinical TUG assessments.

The resident chooses to sit less in the primary living room area and there has been a change in his health leading to a behavior deviation.

Our approach has the ability to distinguish between the behavior patterns of multiple residents in the same room, a limitation that has been cited in studies with environmental sensors [39]. This was especially seen in the case of the couple in the second case study. The two residents have similar gait speed and height which make it difficult to differentiate them using gait parameters such as walking speed, step length, and step time as seen in [39], but they have their own "control centers" or preferred sitting locations, which we can learn and update dynamically. Using the fuzzy clustering approach (with the number of clusters equal to the number of residents living in the apartment), we were then able to distinguish between their differing sitting patterns and detect changes in sedentary behaviors that accompany functional decline of the male resident. We would like to point out here that we have so far tested our system on a single couple. However, this still is a great stride towards detecting individual behavior patterns which has not been explored in previous studies for a multi-person environment.

The strength of our approach is that we were successfully able to continuously collect and analyze behavior in real apartments of older adults for relatively long time periods. Older adults experience functional decline and adverse events over time. It may not be captured in a short observation period of a week, which has been a common time frame used with wearable sensors [1,14,16,18,40,41]. This study highlights the need for studies that analyze these behavior trends over long times to detect the changes that can reflect any functional decline that they may experience.

7. Conclusion and future work

We successfully detected sitting behavior patterns in older adults with different lifestyles (ranging from sedentary to active) and varying functional abilities (using a walker and requiring a caregiver to residents who did not need any functional assistance) over long periods of time. Since the algorithm was tested in real apartment settings, the locations of the chairs and couches varied widely in each living environment. The direction of the sensor to these sitting locations also varied widely for the five residents due to the different layouts of their apartments. We were able to address challenging conditions like multiple residents for a specific case study and handle dynamic environment challenges like occlusion for the five residents described in this work. Our exploratory analysis points to the relationships between temporal changes in routine patterns of sedentary behavior and functional decline of older adults. It highlights the need to continuously monitor these behavior changes in older adults in order to gain useful insights about their mobility, as well as predict their fall risk.

While we do not claim to have the perfect solution for detecting sit-to-stand and stand-to-sit events, this is a great step towards identifying these activities in dynamic and unstructured, and unscripted settings. Our next step is to increase the sample size in order to statistically test our hypothesis with a larger pool of participants. We plan to further explore these activities and test our system on more couples living in independent living facilities to see if we can find their individual patterns through temporal analysis.

In addition to increasing the number of participants, we can explore other more nuanced parameters related to sedentary behavior, such as duration and variability of sitting periods that comprise an individual's daily sitting routine. Another parameter that we have not yet rigorously validated is the actual sit-to-stand time, a known clinical marker of mobility [44]. While this measure has been tested consistently in clinical settings, we need to be careful in measuring this in the home environment since the time itself is less important but the change in time may be a useful biomarker if analyzed over time.

One drawback our monitoring has is that it is confined to the primary living area of the apartments in order to preserve the privacy of our participants. Hence, we cannot account for sedentary activity in other areas (such as bedroom and outside of apartment). However, we can still capture an individual's "baseline" sitting routine and deviations from it. To overcome this limitation, our algorithm can be used in conjunction with sensing modalities of our system located in other parts of the home environment, such as the bedroom where we can capture activities related to sleep behavior using bed sensors [21] and bathroom related activities using radar [20] as well as incorporating more activity related parameters such as gait parameters using acoustic sensors [26] as well as Doppler radars [12,27]. This can provide an even deeper insight into the daily routines of older adults in a non-intrusive manner.

Overall, our approach is strong as it is aligned with current theoretical conceptualizations of sedentary activity [8,32]. Kinect depth cameras can not only identify postural changes associated with sitting but also can detect the specific context of the activity, such as presence of a TV or other people in the apartment that can influence a person's behavior. The ability to capture both the person and the environment advances our understanding of factors amendable to successful clinical intervention [10].

Sedentary activity has the potential to be a new sensitive behavioral marker for functional decline. A low-cost Kinect depth sensor can improve the ability of an in-home activity monitoring system to identify changes that lead to a decline in health of older adults, and alert caregivers of a need for intervention that would lower the cost of healthcare and improve quality of life for an aging population.

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