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The feasibility of a vision-based sensor for longitudinal monitoring of mobility in older adults with dementia

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ABSTRACT

Background: Gait and balance functions decline through the course of dementia, and can serve as a marker of changes in physical status and falls risk. We have developed a technology (AMBIENT), based on a vision-based sensor, which enables the frequent, accurate, and unobtrusive measurement of gait and balance.
Objective: The objective of this study was to examine the feasibility of using AMBIENT technology for frequent assessment of mobility in people with dementia within an inpatient setting. In particular, we examined technical feasibility, and the feasibility of participant recruitment, data collection and analysis.
Methods: AMBIENT was installed in a specialized dementia inpatient unit. AMBIENT captured gait bouts as the participants walked within the view of the sensor during their daily routine and computed the spatiotemporal parameters of gait.
Results: Twenty participants (age: 76.9 ± 6.7 years, female: 50%) were recruited over a period of 6 months. We recorded a total of 3843 gait bouts, of which 1171 could be used to extract gait data. On average, 58 ± 47 walking sequences per person were collected over a recording period of 28 ± 20 days. We were able to consistently extract six quantitative parameters of gait, consisting of stride length, stride time, cadence, velocity, step length asymmetry, and step time asymmetry.
Significance: This study demonstrates the feasibility of longitudinal tracking of gait in a dementia inpatient setting. This technology has important potential applications in monitoring functional status over time, and the development of dynamic falls risk assessments.

1. Introduction

Gait and balance disorders are common consequences of aging and decline in cognitive function (Hausdorff, Rios, & Edelberg, 2001). Impairments of gait and balance are associated with increased risk of falls; people with dementia who have a gait abnormality are approximately three times more likely to fall than those with unimpaired gait (Shaw, 2003). Therefore, information about gait and balance are important factors in an assessment of the risk of falling (Kearns, Fozard, & Nams, 2017; Morgan et al., 2007).

The variability in cognitive and behavioural symptoms and the heterogeneity of dementia challenge the ability of any single cross-sectional assessment to identify those at risk at falling. Most studies of gait and falls in dementia involve cross-sectional assessment in laboratory settings or controlled environments (such as on flat instrumented walkways) that do not reflect the cognitive and physical demands of negotiating real-world environments (Dolatabadi et al., 2018). In addition, physical performance based assessments have feasibility problems in individuals with dementia due to variability in the individuals' motivation, adherence, and comprehension of the task (Sterke et al., 2010; Van Ooteghem et al., 2018). These measures are often poorly sensitive to change (Pardasaney et al., 2012) and lack specificity in people with dementia, most of whom are categorized as high risk. Falls risk assessments are also typically validated over periods

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of 6 months to a year, and thus provide a long-term perspective on falls risk.

The limitations of these approaches have led to the idea of developing a short-term or dynamic falls risk assessment, using frequent or continuous monitoring of mobility functional status, to provide information about fluctuations in risk and opportunities to intervene when the risk is at its highest (Klenk et al., 2017). Recent advances in computer vision sensing and machine learning algorithms have inspired research and development effort towards technologies that can provide dynamic monitoring of gait and balance (Bogo et al., 2016; Cao et al., 2016; Luo et al., 2017; Newell, Yang, & Deng, 2016; Shotton et al., 2011; Sun & Sosnoff, 2018; Toshev & Szegedy, 2014). We have developed a technology, called AMBIENT (Ambient mobility, balance, and gait evaluation and monitoring technologies), for the frequent, accurate, unobtrusive, and cost-effective measurement of gait and balance parameters (Dolatabadi, Taati, & Mihailidis, 2017). AMBIENT consists of vision-based sensors embedded in the environment to automatically detect and track walking sequences of individuals, as well as algorithms and software to compute and analyze spatiotemporal parameters of gait such as step time, step length, walking speed, and symmetry.

We have previously validated AMBIENT against instrumented walkways (Dolatabadi, Taati, & Mihailidis, 2016). AMBIENT has been used to collect and analyse data from individuals with stroke and also people with acquired brain injury (Dolatabadi, Taati, & Mihailidis, 2016, 2017). We have demonstrated that machine learning techniques can analyse AMBIENT data and accurately distinguish impaired gait from healthy gait (Dolatabadi et al., 2017). In a single case study, we also demonstrated that AMBIENT can reliably track changes over time, i.e. either degradation of gait, or improvements with physical rehabilitation (Dolatabadi, Taati, & Mihailidis, 2014).

The aim of this study was to demonstrate the feasibility of the AMBIENT system for frequent and unobtrusive monitoring of gait in older adults with dementia in an inpatient clinical setting. The first question to be addressed was the technical feasibility of study, such as the installation and positioning the sensor within a busy clinical environment, and the protection of the privacy of staff and non-consenting patients on the unit. We also aimed to demonstrate the feasibility of recruitment of research participants within this setting and the acceptability of this research to substitute decision-makers, with a target of at least 60% recruitment rate of eligible participants.

Finally, we evaluated whether the AMBIENT system would be able to capture sufficient longitudinal data, both gait and balance measures and falls outcomes, within this clinical setting and population, to allow the future modelling of dynamic falls risk assessments. To demonstrate the feasibility of this data collection, we assessed the number and frequency of walks, the success rate of recording and parameter extraction, and tracked the number of falls in participants over the data collection period. Our aim was to capture walking bouts (natural or cued) with a minimum frequency of twice a week, with a total number of walks of at least 10 a week, and we predicted a falls rate of 8 falls per month.

2. Study design

2.1. a) Participants

Participants were inpatients in the Specialized Dementia unit at the Toronto Rehabilitation Institute – University Health Network (TRI-UHN), an eighteen-bed inpatient for older adults with behavioural and psychological symptoms of dementia. A clinical diagnosis of dementia is an admission criterion for this unit. Inclusion criteria for the study were diagnosis of dementia based on the clinical record, and ability to ambulate independently (with or without a walker) over a distance of 20 m. There were no exclusion criteria. The duration of participation in the study depended on the interval between recruitment and discharge, and we defined the recording period as the time period from first gait bout recording to last gait bout recording. This study was approved by the Research Ethics Board of the University Health Network. Capacity to consent was established by the unit geriatric psychiatrists. In all cases, participants were found incapable and substitute decision-makers provided written informed consent. Assent from the participant was required before they were engaged in any assessments by the research assistant.

2.2. b) Baseline assessment and follow-ups

At baseline, demographic data (sex and age), type of mobility aid, type of dementia based on medical record, admission Neuropsychiatric Inventory score (Cummings et al., 1994), and history of falls were collected from patient charts. The following assessments were also performed upon enrollment to characterize the study cohort: cognitive performance was assessed by the Severe Impairment Battery-short version (SIBS) (Saxton et al., 2005), functional mobility was assessed by the POMA (Sterke et al., 2010), falls risk was assessed by the STRATIFY falls risk tool (Aranda-Gallardo et al., 2015), and functional status was assessed by the Katz Index of Independence in Activities of Daily Living (KATZ) (Shelkey & Wallace, 1999).

2.3. c) AMBIENT setup

The AMBIENT setup (Fig. 1) consists of a Microsoft Kinect for Windows version 2, a laptop computer (Lenovo ThinkPad P50 s), a Radio-Frequency Identification (RFID) reader (UHF Long Range from FEIG Electronics, Duluth, Georgia, USA), and two circular polarized UHF antennas (Times-7, Wellington, New Zealand). The Kinect sensor was mounted on the ceiling of the hallway. The Kinect sensor tracks the human pose and motion within its field of view at the real-time rate of 30 frames per second (Shotton et al., 2011). As people walk in the field of view of a Kinect sensor, the 3-D locations, i.e., the x, y, and z coordinates, of 25 body parts and joints (head, shoulders, arms, spine, hips, knees and ankles) are tracked. The y axis is aligned with the room vertical pointing upward, the x axis, defines the left and right direction, and the subject's walking direction is along the z axis.

To protect the privacy of staff, non-participating patients, and visitors, the RFID system was used to identify participants in order to automatically turn on Kinect recording when only a study participant was within view. The RFID reader and the laptop were enclosed in a locked wooden box secured the side wall of the hallway. The two RFID antennas were attached on both walls of the hallway and about *8* m away from the Kinect sensor. RFID tags (LinTag™ Heat-Seal, Austin, Texas, USA) with unique ID numbers were assigned to each participant. Following recruitment, the tags were ironed on the patients' pants at knee level with a heat press. A dual-light LED (USB HID Traffic Indicators, Delcom Products Inc., Danbury, Connecticut, USA) was attached to the box to indicate recording status.

2.4. d) Data collection

There were two forms of data collection: natural and cued walks. Natural walks were captured automatically when participants walked within the view of the sensor over the course of the day and night. For cued walks, a research assistant cued the participant to walk on their own towards the system. To distinguish cued walks from natural walks, the research assistant wore an RFID tag with a unique ID. We chose to include cued walks to address the possibility of participants who rarely initiated walking on their own, or who had walking habits that rarely took them to the particular corridor where the system was installed.

2.5. e) Calculation of gait parameters and data analysis

Using a validated methodology (Dolatabadi et al., 2016b, 2014), the following parameters of gait were computed from the smoothed ankle

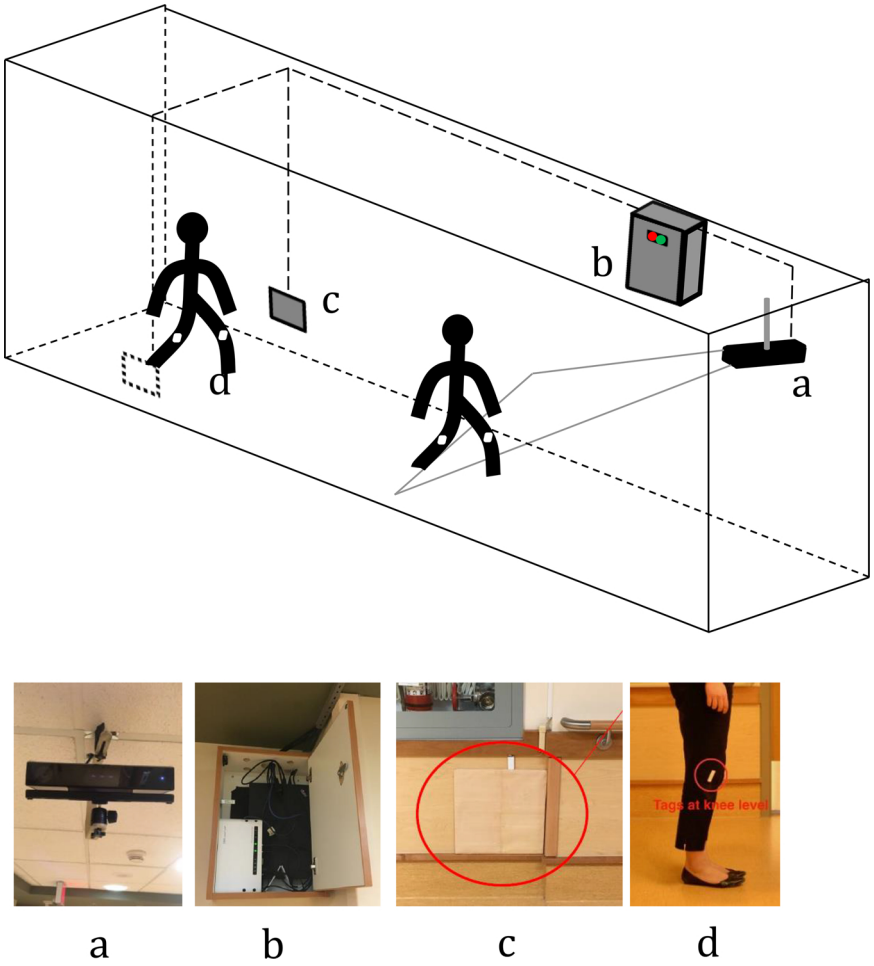

Fig. 1. AMBIENT set-up in the hallway of the Geriatric Psychiatry unit at TRI-UHN. AMBIENT set-up includes a Kinect sensor (a), a control box (b), and two RFID antennas (c). Two RFID tags (d) were attached to participants' clothing at knee level.

and hip trajectories captured by the Kinect sensor: ***step length*** as the displacement of the ankle of one foot along the z axis during stance phase to the ankle of the opposite foot on the previous stance phase, ***step time*** as the elapsed time of double support phase of one foot plus single support phase of the same foot, ***cadence*** as the number of steps per minute, ***gait velocity*** as the displacement of the hip centre along the z axis divided by the elapsed time between the first and last step. Symmetry measures, including ***step time symmetry*** and ***step length symmetry***, were calculated as the ratio of the larger parameter divided by the smaller parameter. The variability measures are calculated as the standard deviation (SD) of each gait parameters within each walking bout divided by the mean value.

We used descriptive statistics to demonstrate our sample characteristics and address our feasibility objectives.

2.6. f) Feasibility assessment

To assess the technical feasibility of the set-up, a log of all technical issues encountered was maintained. We tracked number of eligible participants and decision-makers approached for consent. We reviewed all recordings to identify both unsuccessful recordings and unsuccessful parameter extractions and their causes. We quantified the number of natural and cued walks per participant. We tracked the occurrence of falls during the participants' enrollment in the study. Falls were identified through participation in daily safety huddles, incident reports, and chart reviews. Falls were defined as: "unintentionally coming to rest on the floor or other lower level "and were documented using an approach modified from Yang et al. (2013) We gathered information documented in the chart, and where possible, directly spoke to staff who had witnessed the fall. Information collected about the fall included location of fall, cause of fall, height of fall (e.g. from standing, sitting, or bed), activity at time of fall, direction of fall, and injuries from fall.

3. Results

3.1. a) Technical feasibility

AMBIENT was installed on the inpatient unit as illustrated in Fig. 1. We selected a back corridor of the unit which is not usually crowded, but is commonly navigated by wandering patients. The use of RFID tags allowed us to maintain the privacy of nonconsenting staff and residents by only activating the system when a single participant was in view. In one instance, we discovered that a non-participant was wearing clothes belonging to a participant. We were able to address this promptly by returning the item of clothing to its owner, informing the family of the non-consenting patient, and deleting the recorded walking bouts. There were five incidents in which patients tampered with the equipment (e.g. pulled off the wires or RFID antennae from the wall). We improved the security of the equipment in increments by using better adhesive and camouflaging the antennae using wallpaper the same colour as the walls.

3.2. b) Feasibility of participant recruitment

A total of 64 individuals were admitted to the unit during the 6-

Table 1
Characteristics of Participants.

Characteristics	Participants		
	All (n = 20)	Fallers (n = 8)	Non-Fallers (n = 12)
Sex (Female #)	10	4	6
Age (years)	76.9 ± 6.7	76.9 ± 6.7	76.9 ± 7.1
Height (cm)	165 ± 10	168.1 ± 8.6	163.2 ± 10.7
Weight (kg)	66.5 ± 10.0	65.5 ± 11.6	67.0 ± 9.4
Leg length (cm)	103 ± 20	105.3 ± 23.3	101.7 ± 18.5
Dementia diagnosis (#)			
Alzheimer's	9	2	7
Vascular	2	0	2
Mixed	1	0	1
Lewy Body	1	0	1
Frontotemportal	3	2	1
No specific diagnosis	4	4	0
Admission Neuropsychiatric Inventory (NPI)			
Total NPI	52.9 ± 22.6	52.1 ± 27.4	53.4 ± 20.3
NPI Agitation subscale	10.8 ± 2.4	11.6 ± 1.1	10.3 ± 2.9
Mobility aid (#)			
Wheeled walker	2	0	2
None	18	8	10
Tinetti POMA			
Gait	9.00 ± 2.11	8.4 ± 2.1	9.3 ± 2.1
Balance	10.2 ± 2.9	8.3 ± 1.9	11.3 ± 2.9
Severe Impairment Battery	32.2 ± 15.6	23.4 ± 15.01	35.9 ± 14.9
Katz index	2.3 ± 2.1	1.0 ± 1.1	3.1 ± 2.1
STRATIFY score	2.5 ± 1.1	2.8 ± 1.2	2.4 ± 1.2

month recruitment period, of whom 30 met our inclusion criteria. The main reason for exclusion was use of a wheelchair. All substitute decision-makers agreed to be approached with study information by research staff. Of these, five decision-makers did not return the research staff calls or the consent forms in a timely manner (i.e. the potential participants were nearing discharge by the time we made contact with their decision-makers, thus consent was not pursued). To address this issue, we obtained an amendment to our research ethics approval such that we could initiate data collection with verbal consent from decision-makers over the phone while we waited for the consent form to be returned. During the feasibility study, no decision-maker explicitly declined to provide consent or raised any concerns about the study.

Of the 25 participants initially recruited to the study, five were ultimately withdrawn from analysis—two due to death soon after entry to the study, and three due to a decline in health and walking ability such that they no longer met inclusion criteria soon after entry into the study—leaving 20 participants for analysis. The five excluded participants had 1 ± 1 gait recordings (range 0–3) before their exclusion from the study. Characteristics of the 20 included participants are shown in Table 1. Overall, this represents an 83% recruitment rate and an 80% retention rate in the study.

3.3. c) Feasibility of data collection

We discovered that rollator-type mobility aids interfered with the Kinect skeletal tracking by blocking the lower limbs, however, many individuals who were prescribed rollators or other walking aids did not use them reliably. Ultimately, we excluded 34 walking sequences in which a mobility aid blocked skeletal tracking. Over a period of six months, 3843 Kinect skeletal tracking bouts were captured. Among these, 1906 (49.6%) recordings were discarded for the following reasons:

- Kinect skeletal tracking failure (91% of the discarded video segments). The majority of these (1000 bouts) were discarded because participants were walking away from the sensor and their gait could not be tracked from behind. The sensor sometimes failed to identify the skeleton of participants who walked very close to the wall. Skeleton tracking also sometimes failed for very short participants (height < 110 cm) due to the acute viewing angle of the ceiling-mounted sensor.
- No gait bouts (9% of the discarded video segments). In these cases, the participant triggered the RFID antennas but did not continue walking towards the sensor.

The remaining 1937 bouts amounted to a mean ± SD of 97 ± 84 (median 87.5) walking sequences per person, over a mean length of stay of 48 ± 37 (median 36) days.

We discovered that in order to extract reliable gait measures, a minimum of two gait cycles needed to be captured in the recording. This occurred in 60% of bouts, leaving a total of 1171 recordings, for an average of 58 ± 47 per person. Once the bouts with less than two gait cycles were excluded, the total period of active participation in the study (from the first useable gait bout to last useable gait bout) was reduced to 28 ± 20 days. The descriptive summary of the number of walking recordings for which we were able to extract gait parameters, averaged over 20 participants is shown in Table 2.

We aimed to record walks of participants on at least two days in a week, with a minimum of 10 bouts of walking in a week. As indicated in Table 2, on average, 14 walking bouts including cued and natural walks were recorded per week. However, 15 individuals had < 10 natural walks captured per week, thus necessitating the cued walks. Including both natural and cued walks, 12 individuals had ≥10 walks per week, and all but 1 individual had at least one walk on two or more days per week.

During the six-month study period, there were 21 falls among the participants. The range of reported falls was 0–7, where 12 participants did not fall during their length of stay, three fell once, one fell twice, three fell three times, and one fell 7 times.

3.4. d) Feasibility of data analysis

Table 3 demonstrates the results of the extraction of six gait parameters and their variability measures from the collected AMBIENT data for the feasibility study participants. For summary purposes, the parameters are reported as averaged over all participants over the entire period of data collection, with natural and cued walks reported separately. The mean gait parameters are also divided by fallers and non-fallers. As an illustration of the frequency and variability of selected spatiotemporal gait parameters, Fig. 2 summarizes the data collected from two participants, one of whom fell several times during the study.

Table 2
Summary of number and duration of gait bouts among 20 participants after excluding walks with fewer than 2 full gait cycles.

	Duration*	# cued walks		# natural walks		Duration of bouts
	(days)	Per participant	per week	Per participant	per week	(seconds)
Average ± std	27.7 ± 19.5	32.6 ± 36.5	8.3 ± 7	22.6 ± 24.4	8.6 ± 12.3	3.89 ± 1.11
Range (min-max)	2-76	1-138	1 - 28	2- 90	1 - 81	1 - 11

* Duration from first recorded gait bout to last recorded gait bout.

Table 3
Measures of gait (mean ± standard deviation) averaged over all gait bouts recorded, across all participants, and divided by fallers and non-fallers.

	All (n = 20)	Fallers (n = 8)	Non-fallers (n = 12)
Natural walks			
Step time (s)	0.70 ± 0.09	0.71 ± 0.09	0.69 ± 0.09
Step time variability (%)	9.878 ± 6.51	10.44 ± 6.18	9.12 ± 6.86
Step length (m)	0.41 ± 0.07	0.41 ± 0.07	0.42 ± 0.07
Step length variability (%)	11.08 ± 6.74	11.47 ± 6.22	10.56 ± 7.36
Cadence (steps/min)	88.91 ± 17.6	87.6 ± 10.34	90.66 ± 23.99
Cadence variability (%)	10.52 ± 8.37	11.17 ± 6.81	9.65 ± 10.03
Velocity (m/s)	0.6 ± 0.15	0.59 ± 0.13	0.63 ± 0.17
Step Length Asymmetry	1.22 ± 0.55	1.21 ± 0.16	1.23 ± 0.82
Step Length Asymmetry variability (%)	7.43 ± 7.91	7.76 ± 6.64	7.00 ± 9.34
Step Time Asymmetry	1.19 ± 0.46	1.19 ± 0.15	1.20 ± 0.68
Step Time Asymmetry variability (%)	6.77 ± 7.31	7.1 ± 6.76	6.35 ± 7.97
Cued walks			
Step time (s)	0.67 ± 0.10	0.7 ± 0.09	0.66 ± 0.10
Step time variability (%)	9.56 ± 6.09	10.56 ± 6.17	9.12 ± 6.01
Step length (m)	0.39 ± 0.09	0.4 ± 0.09	0.38 ± 0.09
Step length variability (%)	11.66 ± 7.54	11.94 ± 7.03	11.53 ± 7.76
Cadence (steps/min)	93.25 ± 13.87	88.88 ± 11.09	95.15 ± 14.53
Cadence variability (%)	10.46 ± 8.62	11.42 ± 7.68	10.04 ± 8.98
Velocity (m/s)	0.60 ± 0.18	0.58 ± 0.16	0.61 ± 0.18
Step Length Asymmetry	1.23 ± 0.29	1.22 ± 0.18	1.23 ± 0.32
Step Length Asymmetry variability (%)	8.21 ± 9.12	7.69 ± 6.41	8.43 ± 10.07
Step Time Asymmetry	1.18 ± 0.19	1.19 ± 0.16	1.18 ± 0.20
Step Time Asymmetry variability (%)	6.83 ± 7.33	7.62 ± 6.87	6.48 ± 7.51

4. Discussion

In this study, we have demonstrated that AMBIENT is a feasible vision-based tool for longitudinal monitoring of gait in people with dementia as they move around an inpatient environment. Within the 6-month period of data collection, 1171 walking sequences were recorded, analyzed, and gait parameters successfully extracted. On a daily basis, AMBIENT collected information about individuals' walking patterns during their enrollment in the study. We were able to successfully compute the following gait measures from the recorded walking patterns: mean and variability in step length, step time, cadence, step length symmetry, and step time symmetry, and mean velocity.

When added to existing fall risk factors, quantitative gait and postural-stability measures improve fall risk assessment (Dolatabadi et al., 2018; McGough et al., 2001; Sterke et al., 2012). Individuals with dementia have slower gait, shorter strides, and greater cycle-to-cycle gait variability (McGough et al., 2001; Sheridan et al., 2003; Wittwer, Webster, & Menz, 2010), and these gait impairments predict falls in older adults (Toebes et al., 2012). In particular, stride length variability has been linked to fall risk in older adults both with (Nakamura, Meguro, & Sasaki, 1996; Sterke et al., 2012) and without (Hausdorff et al., 2001; Mbourou, Lajoie, & Teasdale, 2003) dementia. However, most of these studies make use of a single cross-sectional assessment of gait. Two studies have shown that there may be some value to frequent, repeated measurement of a gait in older adults (Kearns et al., 2012; Phillips et al., 2016). One found that the tortuosity of movement path in LTC residents the week before a fall provides a more accurate risk estimate than baseline measurements several months earlier (Kearns et al., 2012). The other found that a decrease in gait speed in community dwelling seniors of 0.05 m/s over 7 days was associated with an 86% probability of an impending fall, compared to 20% probability in those with no change (Phillips et al., 2016).

Frequent monitoring of mobility status allows for better identification of potentially modifiable events in the causal pathway preceding a fall (Klenk et al., 2017). It is significant that some of the known predictors of falls in older adults relate to events that in some way disrupt their homeostasis, such as the initiation of a new medication, a health event, or a hospitalization. For example, observational studies have confirmed that individuals are at high risk of falling in the days and weeks after starting on a new psychotropic medication (Payne et al., 2013). In one LTC study, an acute illness preceded one out of four falls (Boockvar & Lachs, 2003). The onset of delirium is associated with an abrupt worsening in motor performance (Bellelli et al., 2011). Decline in stability of movement may thus be an important biomarker of a decline in the overall resilience and well-being of the individual. If gait and balance functions could be monitored as easily as other vital signs, they could be used to flag an individual who is unwell and at risk of falling, thus allowing for a more precision-based approach to falls prevention in LTC (Rantz et al., 2015). One small pilot study used sensor systems, including gait evaluation, to alert staff to deterioration in function in a residential setting (Rantz et al., 2012). They found that changes in the sensor data were observable 10–14 days preceding 42% of significant health events, and that this facilitated earlier intervention. Although they did not detect a decrease in falls over the course of the study, the intervention group declined less than the control group on functional measures.

The results of this study provide evidence that it is feasible to study and monitor long-term changes in mobility through an unobtrusive vision-based system in an inpatient setting. There has been a move towards the development of sensor-based assessment tools that can monitor changes in quantitative measures of gait and balance repeatedly over time, examples of which include wearable sensors such as accelerometers (Caby et al., 2011). However, there are important limitations to the use of wearable sensors for this purpose, including problems with battery life, data storage, comfort and acceptability, supporting the move towards environmental or vision-based mobility data capture (Dolatabadi et al., 2016b; Parra-Dominguez, Taati, & Mihailidis, 2012; Rantz et al., 2015; Shany et al., 2012).

Through this feasibility study, we have identified several opportunities for improving the AMBIENT technology. While RFID was effective for participant identification, it was also somewhat cumbersome, requiring ironing of tags on clothing. As computer-vision technology further develops, facial recognition would be a way to improve the automatic identification of participants. Furthermore, we found that approximately 50% of recordings were unsuccessful, primarily due to failure in Kinect skeletal tracking. One improvement to the system would be the installation of sensors facing in both directions in the corridor to capture individuals walking both clockwise and counter-clockwise. Replacing the Kinect sensors is another option, possibly with regular video cameras, which are inexpensive and can be used in conjunction with computer-vision and machine learning algorithms to estimate human 3D-joint position from video data (Cao et al., 2016; Newell et al., 2016; Toshev & Szegedy, 2014; Bogo et al., 2016; Luo et al., 2017). A final limitation of the AMBIENT technology at present is that the recorded bouts require some manual processing prior to data extraction. To be a feasible clinical tool, these steps would need to be automated.

In summary, we have confirmed the feasibility of AMBIENT for obtaining frequent and unobtrusive measurements of mobility in older adults with moderate-severe dementia in an inpatient setting. This feasibility study also allowed us to identify several opportunities for improving both the technology and study design. This will guide a future longitudinal observational study of AMBIENT for the development of dynamic falls risk monitoring algorithms.

Declaration of interests

The authors ED, YXZ, AM, and BT certify that they have NO affiliations with or involvement in any organization or entity with any

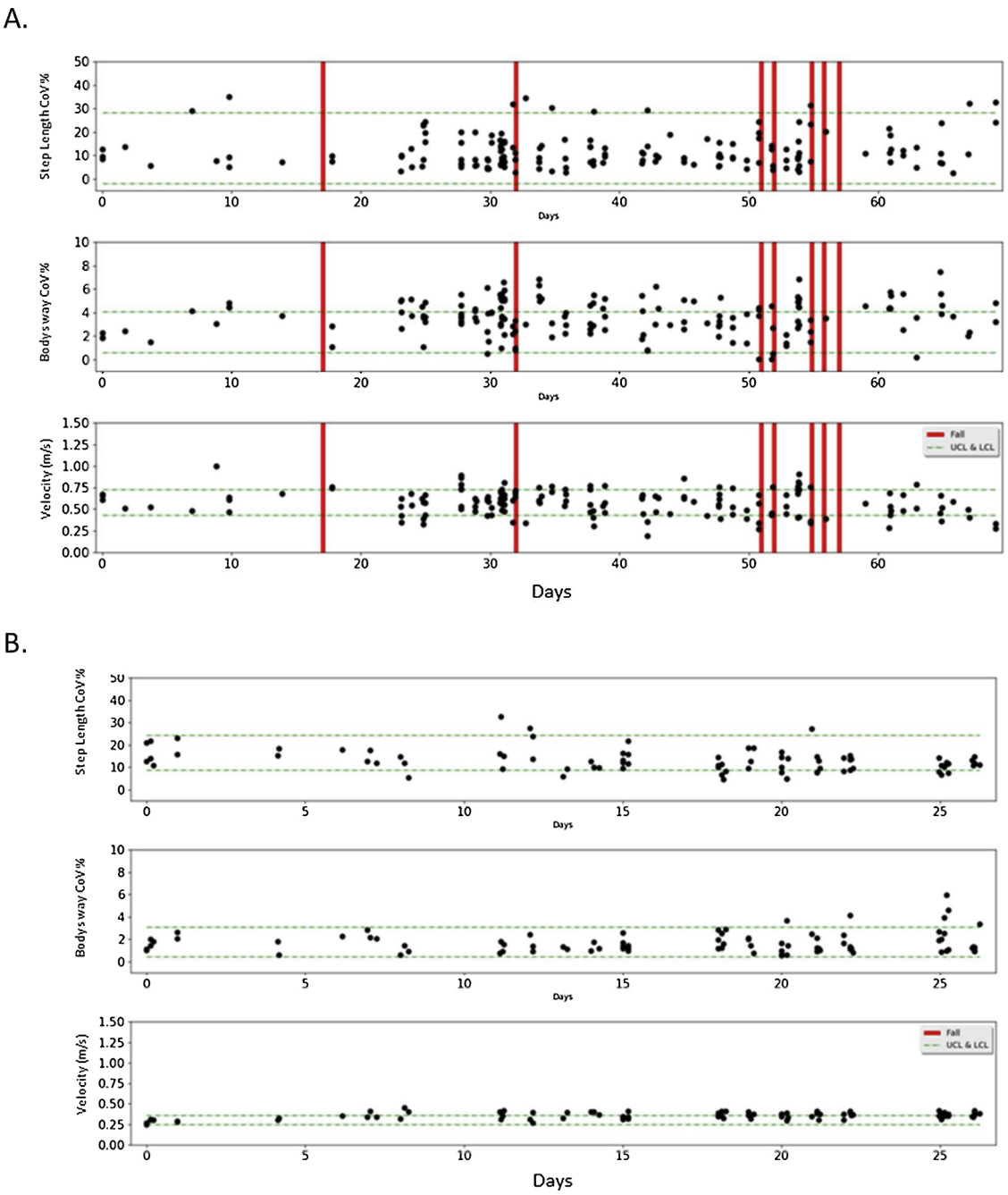

Fig. 2. Control charts illustrating gait data from the feasibility study in two subjects (A + B). Red lines indicate falls and green lines are control limits (± 2 standard deviations) based upon the first seven days of baseline data. CoV = Coefficient of variability, calculated as the standard deviation of the gait quantity within one gait episode divided by the mean of the gait quantity within the same gait episode.

financial interest, or non-financial interest in the subject matter or materials discussed in this manuscript. Outside of the submitted work, AI reports personal fees as a scientific advisor to Winterlight LLC; AJF reports grant support from US National Institute of Health, the Patient-Centered Outcomes Research Institute, the Canadian Institute of Health Research, Brain Canada, and the Ontario Brain Institute.

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