September, 2012

Path tortuosity in everyday movements of elderly persons increases fall prediction beyond knowledge of fall history, medication use, and standardized gait and balance assessments.

William D. Kearns, PhD, *University of South Florida*
James L. Fozard, PhD, *University of South Florida*
Marion Becker, RN/PhD, *University of South Florida*
Jan M. Jasiewicz, PhD
Jeffrey D. Craighead, PhD, et al.

JAMDA 13 (2012) 665.e7–665.e13

JAMDA

journal homepage: www.jamda.com

Original Study

Path Tortuosity in Everyday Movements of Elderly Persons Increases Fall Prediction Beyond Knowledge of Fall History, Medication Use, and Standardized Gait and Balance Assessments

William D. Kearns PhD [a,*], James L. Fozard PhD [b], Marion Becker RN, PhD [c], Jan M. Jasiewicz PhD [d], Jeffrey D. Craighead PhD [d], Lori Holtsclaw BA [b], Charles Dion MA [e]

[a] *Department of Rehabilitation and Mental Health Counseling, USF College of Behavioral and Community Sciences, Tampa, FL*
[b] *School of Aging Studies, USF College of Behavioral and Community Science, Tampa, FL*
[c] *School of Social Work, USF College of Behavioral and Community Sciences, Tampa, FL*
[d] *VA HSR&D/RR&D Research Center of Excellence on Maximizing Rehabilitation Outcomes, James A. Haley Veterans' Hospital, Tampa, FL*
[e] *Policy and Services Research Data Center, Department of Mental Health Law and Policy, Florida Mental Health Institute, USF College of Behavioral and Community Sciences, Tampa, FL*

Keywords:
Falls
telemedicine
standardized gait and balance
psychoactive medications
assisted living facilities
movement variability, elderly
telesurveillance

A B S T R A C T

Objectives: We hypothesized that variability in voluntary movement paths of assisted living facility (ALF) residents would be greater in the week preceding a fall compared with residents who did not fall.
Design: Prospective, observational study using telesurveillance technology.
Setting: Two ALFs.
Participants: The sample consisted of 69 older ALF residents (53 female) aged 76.9 (SD ± 11.9 years).
Measurement: Daytime movement in ALF common use areas was automatically tracked using a commercially available ultra-wideband radio real-time location sensor network with a spatial resolution of approximately 20 cm. Movement path variability (tortuosity) was gauged using fractal dimension (fractal D). A logistic regression was performed predicting movement related falls from fractal D, presence of a fall in the prior year, psychoactive medication use, and movement path length. Fallers and non-fallers were also compared on activities of daily living requiring supervision or assistance, performance on standardized static and dynamic balance, and stride velocity assessments gathered at the start of a 1-year fall observation period. Fall risk due to cognitive deficit was assessed by the Mini Mental Status Examination (MMSE), and by clinical dementia diagnoses from participant's activities of daily living health record.
Results: Logistic regression analysis revealed odds of falling increased 2.548 ($P = .021$) for every 0.1 increase in fractal D, and having a fall in the prior year increased odds of falling by 7.36 ($P = .006$). There was a trend for longer movement paths to reduce the odds of falling (OR .976 $P = .08$) but it was not significant. Number of psychoactive medications did not contribute significantly to fall prediction in the model. Fallers had more variable stride-to-stride velocities and required more activities of daily living assistance.
Conclusions: High fractal D levels can be detected using commercially available telesurveillance technologies and offers a new tool for health services administrators seeking to reduce falls at their facilities.

Risk of falling and fear of falling increase sharply in community dwelling adults, particularly for those in their eighties.[1] The risk of falls for same aged residents in nursing homes is estimated to be 2 to 3 times greater.[2–4] Falls are expensive adverse events for the elderly, costing the US economy over $19 billion in 2000 and cost estimates increase to $55 billion by 2020.[5] Wagner and colleagues [6] note that even though falls are the most frequent adverse event in nursing homes, there is little consistency in reporting contributing factors. Most falls are related to faller predispositions to unsteadiness, impaired gait, muscle weakness, impaired cognitive and sensory functioning, and prior fall history. [2–4,7] The mix of environmental and predisposing factors for falls and available preventive measures vary widely across living situations.[8,9] Antipsychotic and antidepressant drugs contribute to fall risk by affecting cognitive and perceptual motor processes. In a large study of fall risk in nursing homes, French et al[10] identified 18 fall risk factors;

The authors of this manuscript attest there were no conflicts of interest present in the conduct of this research or the preparation of this manuscript.

Support was provided by Agency for Healthcare Research and Quality R21HS18205-01, 'Evaluation and Integration of an Automatic Fall Prediction System.'

* Address correspondence to William D. Kearns, PhD, Department of Rehabilitation and Mental Health Counseling, USF College of Behavioral and Community Services, 13301 N. Bruce B. Downs Blvd, Tampa, FL 33612.
E-mail address: Kearns@usf.edu (W.D. Kearns).

1525-8610/$ - see front matter Copyright © 2012 - American Medical Directors Association, Inc.
http://dx.doi.org/10.1016/j.jamda.2012.06.010

the top three—unsteady gait, need for extensive assistance in activities of daily living (ADL), and wandering—were related to movement patterns. In community based studies, increased variability in stride to stride velocity has been identified as a potent risk factor for subsequent falls in persons with and without cognitive impairments.[11−13]

Changes in the quality and quantity of movement are prominent features associated with changes in health, medication regimens, cognitive impairment, and other predisposing factors involved in fall risk.[14] As a practical matter, it is difficult to identify what, when, where, or how the changes in movement patterns leading up to the fall event occur. The major hypothesis of the present research is that movement patterns associated with fall risk will occur close in time to the fall event. To evaluate the hypothesis, the voluntary movement paths of persons traveling within the common areas of an assisted living facility (ALF) were monitored with a ultra-wideband telesurveillance system described in the Methods section and in earlier publications.[15,16] Briefly, changes in the location of a transponder worn by the person are consolidated into paths, each bounded at the beginning and end by a 60-second period of inactivity. The distance, duration, velocity, and vector changes in each movement path are automatically calculated and cumulated over time using Craighead's real-time fractal path analysis algorithm.[17] Random changes in path direction reflecting uncorrelated turns increase the path's "tortuosity" and are captured in the fractal dimension (fractal D) measure, which ranges from 1.0 when a movement path is perfectly straight (and therefore can be described by a line having solely the dimension of length) to a value of 2.0 when the path is so tortuous (eg, a "drunkard's walk") that fully two dimensions of a plane (length and width) are required to describe it. We hypothesized that the contribution of path tortuosity to fall risk would improve estimates beyond that provided by previously identified fall risk factors: age,[1] impaired gait and balance,[18−20] prior fall history, [6,10,21] number of ADL requiring supervision or assistance in community,[1,6] impaired cognition,[20] and the use of cardiac and analgesic medications,[22,23] antidepressants,[24,25] and antipsychotics.[10,26]

To our knowledge, there are no published data on falls among residents in ALFs, which provide hotel services and assistance with ADLs,[27] but not nursing services. Kallin et al[7] report a Swedish study of falls in residential care facilities for elderly persons that included various settings from independent living apartments to skilled nursing home care and specialized dementia care units. Following a baseline assessment, 140 women and 59 men in the various settings named were followed for a year; approximately 57% had one or more falls during the observation period, a figure slightly lower than that reported for nursing homes in the United States. Falls involving voluntary movement were our primary focus. Falls are defined as an unintended movement from an elevated position to a position on the surface on which the person was either standing or from a higher surface such as a chair, with no elaboration of the circumstances surrounding the fall. [28,29] In prospective fall risk studies in community and some nursing homes, self-report provides the basis for defining injury related falls.[1,8,30]

In Kallin et al,[7] a team comprising a physician, nurse and a physiotherapist determined fall circumstances using faller self-reports and eyewitness accounts. In the present study, fall information was obtained from records maintained by state of Florida licensed ALFs providing data on when and where the fall occurred, precipitating circumstances as provided by staff or self-report, and the fall's consequences. Because the focus of the study on relating movement patterns to falls, the present study restricted the definition of a fall to investigators' consensus that the fall occurred during active voluntary movement and not simply sliding from a chair or bed as when dozing or resting.

In summary, the present study investigated the relationship of falls by ALF residents over a 1-year observation period to their movement path variability over the same period. The main hypothesis tested was that movement path variability would be greater in persons the week before they fell compared to those not experiencing a fall. To evaluate the hypothesis a novel adaptation of location aware telesurveillance technology capable of measuring small directional changes, rate of travel and duration of free movements over long durations[16] was employed. The contribution of these movement dimensions to fall risk was investigated in the context of previously established risk factors for falls.

Methods

Participants

Sixty-nine ALF residents (53 female) aged 76.9 (SD ±11.9 years) with a mean Mini Mental Status Examination (MMSE) of 18.3 (SD ± 7.2) participated in the study. Following University of South Florida Institutional Review Board approval, recruits were informed that the study would examine health changes related to movement patterns over 1 year monitoring interval using a small lightweight transponder, and their ALF records would be monitored for fall incidents, medications, and health changes. They were informed they would receive a standardized gait and balance (SGB) assessment and short test of cognitive ability at the study's start, and the results would be placed in their ALF health records. Proxy consent was obtained for those unable to provide informed consent.

Creation of the Faller and Non-Faller Contrast Groups

Participants' classified as *fallers* had at least one validated fall (fell while ambulating during the monitoring interval) and had tracking data in the 7 prior days. *Non-fallers* had no validated falls; their monitoring interval's midpoint date was substituted and tracking data from the 7 days prior were used. This procedure yielded 23 fallers and 30 non-fallers for analysis (16 could not be classified using the validation protocol); their characteristics of these 53 mirrored the full group (83% female, mean MMSE = 18, SD ± 7 and mean age, 76.6 years, SD ± 11.5) (Table 1).

Apparatus

Movement Path Data

A Ubisense ultra-wideband real-time location system (Ubisense Corp., Cambridge, UK) with four sensors was installed in two ALFs in a roughly rectangular configuration.[16] Every participant was assigned one Ubisense compact tag. Some participants with moderate cognitive impairment who routinely removed tags were provided with Wanderguard, Inc. (Stanley Healthcare Solutions, Lincoln, NE) locking wrist straps to reduce data loss. Twenty-six participants (38%) disliked wearing wristbands. Prior testing[15] revealed no significant differences between positional data generated from tags on wrist

Table 1
Demographic Characteristics of Faller and Non-Faller Groups.

Characteristic	Fallers n = 23	Non-Fallers n = 30
% Female	82.6	83.3
Age (±95% CI)	75.61 (±4.60)	75.40 (±4.29)
MMSE (±95% CI)	16.8 (±3.08)	19.00 (±2.34)
% Hispanic	8.7	3.3
% Black	4.3	10.0
ADL's needing assistance (+/− 95% CI)	3.91 (±0.92)	2.50 (± 0.60)
% With dementia diagnosis	47.8	60.0

straps or on personal assistive devices required for ambulation, so for these participants the tag was attached to their personal assistive devices. Tag position data were recorded on a notebook computer running Ubisense Platform v. 2.1.7. A movement path was defined as an episode of tag movement with 60 seconds of no movement at start and finish; periods of inactivity less than 60 seconds were considered part of the movement path. Custom written software, "FractalTracker," implementing Craighead's real-time fractal path analysis (RTFPA) algorithm[17] calculated fractal D for each movement path. The calculated fractal dimension value represents the degree of nonlinearity of a path between two points in space. RTFPA calculates this value by estimating the path length using multiple minimum units of length (spatial scales). These spatial scales vary along the path as a multiple of the mean distance between points that make up the path. These estimated path lengths are then transformed using the following function: f (length, scale) = log (length)/log (scale). D is the slope of the line between two estimates on a log/log plot of estimates transformed by the previous function. RTFPA takes path duration, rate, and total distance into account as rate of travel directly affects the spatial scales used in the estimation of the total path length at the various spatial scales and this path length is a function of rate and path duration. Section 3 of Craighead's article[17] provides a detailed discussion of the RTFPA implementation, and a comparison to other algorithms for estimating D. Movement path duration, rate and distance were also recorded. Data acquisition was remotely managed at each site and automated scripts daily uploaded data to HIPAA compliant storage at the University of South Florida.

Orientation Sensor

During SGB (J.J.) participants wore a wireless 9 df orientation sensor, (Inertia Cube 3 (IC3), Intersense, Billerica, MA) containing three rate gyroscopes, three uniaxial accelerometers, and three magnetometers.[31] Maximum static accuracy at 255Hz update rate was 0.25° in pitch and roll, and 1° in yaw, with pitch aligned with the body COM sagittal axis thus representing forward and backward sway. The IC3 was attached to each participant at S1/L5, which is the approximate location of COM. We assumed that the trunk was a rigid segment. An 8 m GaitRite instrumented mat (CIR Systems, Clifton, NJ) calculated gait parameters.[32,33]

Procedure

The SGB assessment and MMSE[34] were administered at recruitment. The SGB assessments consisted of several parts. Static balance—standing but not moving—was assessed with a modified clinical test of sensory interaction on balance (mCTSIB)[35] that included four conditions: (1) eyes open standing on solid surface;(2) eyes closed on solid surface; (3) eyes open standing on a foam pad; and (4) eyes closed standing on foam pad. Dynamic balance was assessed by the Timed Get Up and Go Test[36,37] and the Timed 180° Turn Test.[38] Gait velocity was determined by the Dual Task Walking Test.[39] Cognitively impaired participants unable to understand instructions were not tested. The Timed Get Up and Go Test required participants to rise unassisted, walk rapidly unaided 3 m, turn about a cone without touching, return, and sit. Participants requiring walking aids, or unable to rise unassisted were excluded. Trials completed, duration, maximum and mean turn rate at cone and chair were recorded. In the 180° Turn Test the participant was asked to rotate exactly 180° while standing. Trials completed, degrees rotated, number of steps and time to complete the turn were recorded. For the Walking Test participants strode self-paced 8 m on a gait mat under single task (no cognitive load) or a dual task condition in which the participant listened to a randomized audio sequence for "X", and repeated the letter aloud. Number of strides, stride velocity, and coefficient of variation (COV), time to traverse the mat, and trials completed were recorded. Sway (IC3) was recorded during all tests, and the SGB test-presentation order was randomized. Subjects received a minimum of 3 minutes rested between different SGB tests and at least between 30 and 45 seconds of rest between each trial within a SGB test.

Tracking Data Collection

Following SGB assessment each participant was instructed to wear their tag during waking hours but remove it for bathing; those with tags on assistive devices were asked to not remove it. Participants were told the tag emitted weak radio signals revealing its location only in the common area between domiciles and the dining area. Data quality control occurred thrice weekly; missing data lasting more than a day resulted in an email message to the ALF operator with a request to determine if tag failure or protocol noncompliance was at issue; in the first instance the battery or tag was replaced and in the second the participant was counseled to resume wearing the tag. The tag was worn for as long as the person was in the study; not every subject completed the year-long participation; some dropped out because of illness, death, or movement to a higher level of care.

Fall Validation Protocol

Investigators (W.K., J.F., M.B., and J.J.) independently evaluated fall records to identify falls occurring while ambulating, attempting to stand or transferring, but not sliding from one's seat or bed to the floor; 75% investigator agreement was required. Fall incident reports for the baseline year preceding the study were evaluated using the same criteria.

Medications and Clinical Diagnosis of Dementia

Medication prescription start and stop dates from ALF records were extracted for baseline and observation periods. Medications were classified as psychoactive by an RN/PhD in psychiatric nursing (M.B.). Participant's clinical diagnosis of dementia was also extracted.

Activities of Daily Living

Standardized ADL assessments of ambulation, bathing, dressing, toileting, eating, and transferring, characterizing the participant as "independent," "needs supervision," "needs assistance," or "needs total help" were obtained from ALF records and coded by assessment date closest to the beginning of the observation period.

Data Reduction and Statistical Analyses

Of 69 participants recruited, seven died, four were discharged to skilled nursing, hospice or other care facilities, and nine voluntarily discontinued participation. For the majority of these participants, ultra-wideband data acquisition was cut-short by a fall, the focal event of the study. Close examination of their data indicated they did not differ significantly from the 49 who completed all 365 days; mean number of observation days for these 20 participants was 204.2 (SD ± 91.6, range 78–348). Therefore, the data for the 20 participants were included for analysis. From these 69 subjects, 53 were selected according to the protocol described previously in the Participants section of the Methods section.

Results

Static Balance – mCTSIB

The foam surface condition proved markedly more difficult than the firm surface for both groups, but the mCTSIB and (IC3) sway area failed to differentiate fallers and non-fallers. The mean number of trials successfully completed by fallers and non-fallers on the firm surface condition with eyes open was 2.26 trials (SD ± .96) vs 2.07

(SD ± 1.01; t = .71 df = 51 P = n.s), and for eyes closed (fallers) 2.0 trials (SD ± 1.24) vs (non-fallers) 1.7 trials (SD ± 1.24; t = .87 df = 51 P = n.s). For the foam surface eyes open condition fallers completed .39 trials (SD ± 1.03) and non-fallers .40 (SD ± .85; t = .03 df = 51 P = n.s.). The eyes closed foam condition also failed to differentiate the groups (faller mean = .39, SD ± 1.03 vs non-faller mean = .27, SD ± .69, t = .53 df = 51 P = n.s.).

Dynamic Balance

Measures were available for just 17 fallers and 20 non-fallers on the Timed 180° Turn Test and for 15 fallers and 15 non-fallers on the Timed Get Up and Go Test; neither test differentiated fallers from non-fallers.

Gait

Twelve fallers and 22 non-fallers completed gait testing (Walking Test); mean stride velocity and trials completed did not differentiate fallers and non-fallers. No main or interaction effects of dual tasking on stride velocity were observed but stride velocity COV was significantly greater for fallers under both single and dual-task conditions (faller mean COV = .151 (95% CI ± .0161) vs non-faller COV = .111 (95% CI ± .0136) t = 3.54 df = 32 $P < .001$;) and dual task conditions (faller mean COV = .161 (95% CI ± .0336) vs non-faller COV = .119 (95% CI ± .0176) t = 2.40 df = 32 $P < .023$).

Fractal D, Fall History, and Psychoactive Medications

Preliminary analyses demonstrated that age and gender did not differentiate fallers and non-fallers either when used alone in logistic regressions or when combined with the variables discussed below. Using each participant's fall index date or midpoint index date (for non-fallers), a logistic regression was computed in which four predictors were tested for their ability to differentiate fallers from non-fallers:

- Average fractal D from movement paths recorded 7 days prior to the index date
- Mean movement path length recorded for the same intervals
- One or more recorded falls in the study's baseline year (yes/no)
- Number of psychoactive medications prescribed at the time of the index event

Results of the logistic regression revealed odds of falling increased 2.548 (P = .0209; 95% CI 1.152–5.635) for every 0.1 increase in fractal D, while a fall in the prior year increased odds by 7.360 (P = 0.0063; 95% CI 1.760–30.785). A nonsignificant trend for physically longer movement paths to reduce odds of falling was observed (OR = .976 P = .08; 95% CI 0.949–1.003), but number of psychoactive medications did not significantly increase odds of falling (OR = .97, P = .8897; 95% CI 0.626–1.502). The overall model correctly classified 80% of fallers and non-fallers. As predicted mean fractal D levels were significantly higher in fallers than non-fallers (1.30 vs 1.25; t = 1.725 df = 51 P = .045 [one tailed]). Auxiliary analyses revealed none of the other dimensions of movement differentiated fallers from non-fallers, although a negative relationship of fractal D with rate of travel (r = −0.54, n = 53 $P < .001$) was similar to a finding reported earlier.[16] Figure 1 shows the probability of a fall in relation to the average fractal D in the week prior to the fall when the other statistically significant risk factor, one or more validated falls during the baseline period, was positive or negative.

Figure 2 presents the results predicting a fall from the fractal D movement variability measure alone.

Changes in Fractal D Over Time

Possible changes in fractal D over the total period of time leading up to the fall were evaluated using correlational analyses. The mean fractal D 1 week before the fall correlated r = .67, n = 53 $P < .05$ with the fractal D recorded in the first week of the study and r = .97, n = 53 $P < .01$ with the mean fractal D in the second (adjacent) week preceding the fall. Neither the first week of the study's recorded mean fractal D nor the measure recorded 2 weeks before the fall was reliably associated with the future fall.

Relationship of Fractal D to SGB Measures

Fractal D was correlated with number of steps (r = .34 n = 37 $P <$ .05) and time (r = .47 n = 37 $P < .01$) required to complete the 180°

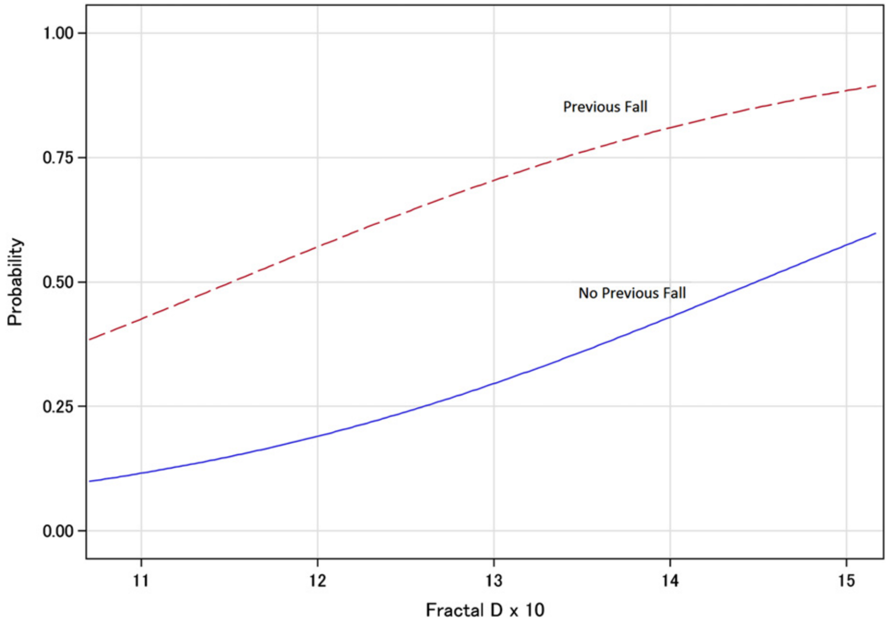

Fig. 1. The predicted probability of a fall by average fractal D measurement (×10) from the 7 days prior to the fall or non-fall index event stratified by presence of previous fall.

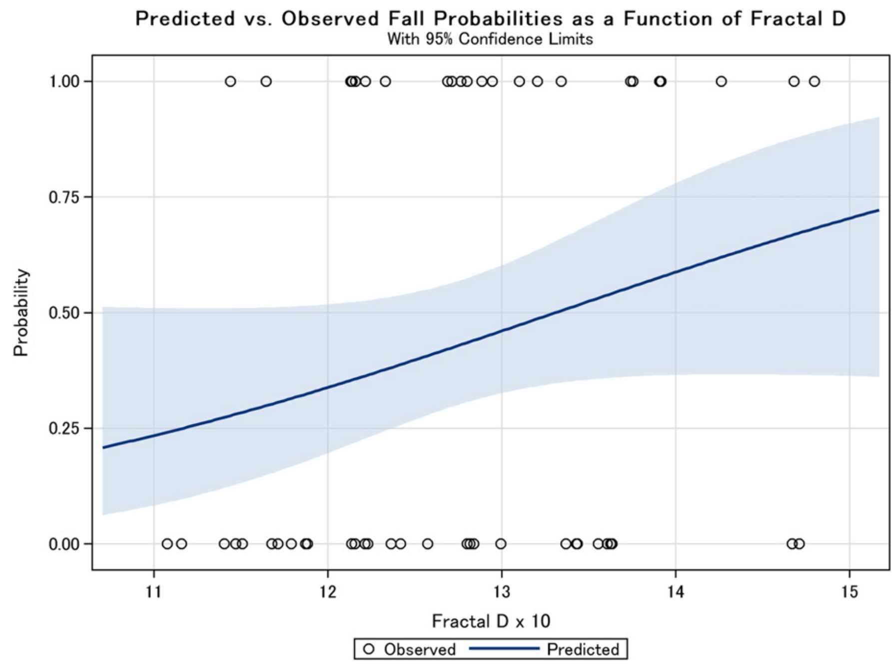

Fig. 2. The predicted probability of a fall by average fractal D measurement (×10) from the seven days prior to the fall or non-fall index event along with the 95%CI from the logistic regression model including only fractal D in the model.

Turn Test, and negatively correlated with the number of degrees rotated ($r = -.34$ $n = 37$, $P < .05$), and (IC3) sway area ($r = -.37$ $n = 37$ $P < .05$). Fractal D correlated positively ($r = .36$ $n = 37$ $P < .05$) with the time required to complete the Get up and Go Test and positively with Walking Test Dual Task stride to stride velocity COV ($r = .31$ $n = 34$ $P < .04$ [one-tailed]). For the mCTSIB, fractal D was weakly correlated ($r = -.24$ $n = 53$ $P < .05$ [one-tailed]) with the number of trials completed while standing with eyes open on a foam surface. No other measures were related to fractal D.

ADLs, Dementia Diagnosis, and MMSE

Fallers and non-fallers differed significantly in total ADLs requiring assistance (faller mean = 3.91 non-faller = 2.50, $t = 2.605$ $df = 51$ $P < .05$) and ADLs independent (faller mean = 2.00 non-faller = 3.40, $t = 2.92$ $df = 51$ $P < .01$) but not in ADLs requiring supervision (faller mean = 1.13 non-faller = 1.17 $t = 0.09$ $df = 51$ $P =$ n.s.). No significant association was found between falls and dementia diagnosis ($\chi 2 = .779$ $df = 1$ $P =$ ns) or MMSE scores (faller mean = 16.8 non-faller mean = 19.0, $t = 1.14$ $df = 51$ $P =$ n.s.), however MMSE scores were negatively correlated with fractal D ($r = -.36$ $n = 53$ $P < .01$), confirming prior observations.[16]

Discussion

The major finding is that fractal D, a measure of path tortuosity obtained by telesurveillance technology, is an independent predictor of future falls after past fall history is taken into account. There was no significant association of number of psychoactive medications and elevated fall risk. This is perhaps attributable to the observation that 51 out of 53 participants had psychoactive medications prescribed at the time of their index event resulting in a truncation of range combined with small sample size. Most importantly, the accuracy of fall prediction (vertical axis) provided by knowledge of past fall history and fractal D is cumulative as shown in Figure 1. A history of falls increases the probability of a fall (vertical axis) at all levels of fractal D (horizontal axis). Figure 2 shows that low fractal D levels are associated with lower fall probabilities; the practical significance is that the addition of a continuous dynamic assessment of everyday movement patterns obtained automatically and unobtrusively significantly improves the accuracy of fall risk estimates beyond that provided by other known predictors. In congregate living settings such as nursing homes and ALFs the costs of the location aware technology are relatively low by virtue of economies of scale, since the infrastructure need not be pervasive and may be located just in publicly accessible areas. Individual tag costs are low and over 100 tags can be monitored simultaneously using this approach.

While there was a significant difference in fractal D for fallers and non-fallers, the results do not indicate when group differences emerged. Fallers and non-fallers did not differ significantly at the time of the first week of the study but were significantly different at the time of the fall. This change was not readily predictable nor was it linked to the time, which had elapsed preceding the fall. For the fallers the correlation between fractal D in the 7 days immediately preceding the index event with fractal D in the week prior was 0.97, but was only 0.67 with participants' measures the first week of the study. The results are consistent with our hypothesis that fractal D delivered by the online monitoring system is more predictive of falls in the near future than in the more distant past. Our approach is analogous to the use of an onboard flight "black-box" data recorders that are used to better understand events leading up to aircraft accidents.

Fallers and non-fallers did not differ on MMSE, but the negative correlation of MMSE with fractal D accounting for about 16% of the shared variance previously reported by Kearns et al was confirmed.[15,16] Tzeng[40] found 34% of patients who fell in a hospital setting had mental status deficiencies, however, the contribution of cognitive impairment to fall risk remains unclear. The number of ADLs requiring assistance was significantly higher in our fallers while greater ADL independence distinguished non-fallers, consistent with published findings.[6,10] Fallers and non-fallers did not differ on static or dynamic balance measures, although fewer successful trials on the foam surface condition for both groups was consistent with other studies, as was the eyes open vs closed difference.[40,41] The negative

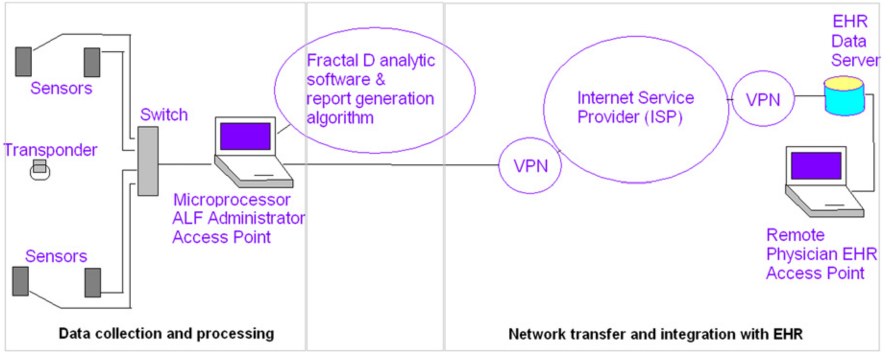

Fig. 3. Conceptual diagram illustrating how the fall risk assessment telesurveillance system would operate in practice.

correlation of fractal D with the *180° Turn Test* measures indicates that high fractal D participants make incomplete turns and take longer to do so. Difficulties making a turn even when specifically instructed may reflect navigational errors during normal movements that contribute to increased path tortuosity. We have found fractal D is *inversely related to MMSE geographic orientation* scores[16] indicating spatial confusion.

Gait

Our failure to find that adding a cognitive task increases variability in step lengths, stride times, and stride velocities likely reflects the choice of too easy a cognitive task and a drop in statistical power. Fractal D was significantly correlated with stride time COV and fallers had higher COV than non-fallers, results similar to those of Priest et al[42] using similar methodology and instrumentation. For frail elders for whom gait and balance tests are too difficult, fractal D may be an appropriate predictor of future falls in assisted living facilities.

Conclusions and Practical Applications

We have demonstrated that an automatic dynamic quantitative assessment of the variability of everyday movements is an independent predictor of fall risk which, when combined with other known risk factors for falls, can significantly improve the accuracy of fall prediction beyond that possible by other risk factors alone. Because of the large number of residents in most nursing homes and ALFs, a system that provides continuous assessment of changes in path tortuosity before a fall may be a useful addition to the current procedures used to predict fall risk.

The major practical issue with using a system concerns where, when, and the form the information from the system would take when provided to the facility operator and clinicians involved in the resident's care. Figure 3 (above) displays one scheme illustrating how the information could be used. Two computer icons appear in Figure 3; one is used by the ALF operator and provides a digest of daily fractal D scores for the ALF residents and presents information on residents' other risk factors. The second computer provides information about selected residents to their personal attending physicians whose main concern might include monitoring for side effects of their patient's prescribed medications. The left side of the diagram represents the equipment used to track movements, store and process the data. The center and right sides of the diagram represent the network transfer and integration of data into one or more electronic health record systems.

In the present research, the operation of the data collection and processing system was remotely monitored and managed. Computer and network system failures, battery failures, malfunctioning, lost and unworn transponders were all detected remotely and corrective actions were taken including the sending of remedial instructions to the operator of the ALF. The data in the case of the present research were automatically uploaded as a file to a remote site for additional processing; a similar protocol could be employed if the data were being sent via a secure link to an electronic health record (EHR) to be appended to the individual's electronic health record.

Acknowledgment

The authors thank the anonymous reviewers for their constructive comments.

References

1. Schiller JS, Kramarow EA, Dey AN, National Center for Health Statistics (US). Fall Injury Episodes Among Noninstitutionalized Older Adults, United States, 2001–2003. US Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics; 2007.
2. Rizzo J, Friedkin R, Williams C, et al. Health care utilization and costs in a Medicare population by fall status. Med Care 1998;36:1174.
3. Rubenstein LZ, Josephson KR, Robbins AS. Falls in the nursing home. Ann Int Med 1994;21:442.
4. Rubenstein LZ. Falls in older people: Epidemiology, risk factors and strategies for prevention. Age Ageing; 2006. http://dx.doi.org/10.1093/ageing/afl084.
5. Stevens J, Corso P, Finkelstein E, Miller T. The costs of fatal and non-fatal falls among older adults. Inj Prev; 2006. http://dx.doi.org/10.1136/ip.2005.011015.
6. Wagner LM, Scott V, Silver M. Current approaches to fall risk assessment in nursing homes. Geriatr Nurs 2011;32:238–244.
7. Kallin K, Jensen J, Olsson LL, et al. Why the elderly fall in residential care facilities, and suggested remedies. J Fam Pract 2004;53:41–54.
8. Tinetti ME, Doucette JT, Claus EB. The contribution of predisposing and situational risk factors to serious fall injuries. J Am Geriatr Soc 1995;43:1532–5415.
9. Jensen J, Lundin-Olsson L, Nyberg L, Gustafson Y. Fall and injury prevention in older people living in residential care facilities: A cluster randomized trial. Ann Intern Med 2002;136:733–741.
10. French DD, Werner DC, Campbell RR, et al. A multivariate fall risk assessment model for VHA nursing homes using the minimum data set. J Am Med Dir Assoc 2007;8:115–122.
11. Yogev-Seligmann G, Hausdorff JM, Giladi N. The role of executive function and attention in gait. Movement Disord 2008;23:329–342.
12. Verghese J, Holtzer R, Lipton RB, Wang C. Quantitative gait markers and incident fall risk in older adults. J Gerontol A Biol Sci Med Sci 2009;64A:896–901.
13. Hayes TL, Pavel M, Kaye JA. An unobtrusive in-home monitoring system for detection of key motor changes preceding cognitive decline. Conf Proc IEEE Eng Med Biol Soc 2004;4:2480–2483.
14. Kearns WD, Fozard JL, Lamm RS. How knowing who where and when can change healthcare delivery. In: Röcker C, Ziefle M, editors. Human Centered Design of e-Health Technology: Concepts, Methods and Applications. Hershey, PA: IGI Global; 2011. p. 139–160.
15. Kearns W, Nams V, Fozard J. Wireless fractal estimation of tortuosity in movement paths related to cognitive impairment in assisted living facility residents. Methods Inf Med 2010;49:592–598.
16. Kearns W, Nams V, Fozard J, et al. Wireless telesurveillance system for detecting dementia. Gerontechnology 2011;10:90–102.

17. Craighead JD. Using fractal dimension to assess robot operator skill in a search task. J Intell Robot Syst 2011;64:97–118.
18. Hill K, Schwarz J, Flicker L, Carroll S. Falls among healthy, community-dwelling, older women: A prospective study of frequency, circumstances, consequences and prediction accuracy. Aust N Z J Public Health 1999;23:41–48.
19. Hausdorff JM. Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking. Human Movement Sci 2007;26: 555–589.
20. Hausdorff JM, Balash J, Giladi N. Effects of cognitive challenge on gait variability in patients with Parkinson's disease. J Geriatr Psychiatry Neurol 2003;16:53–58.
21. Maki B. Gait changes in older adults: Predictors of falls or indicators of fear. J Am Geriatr Soc 1997;45:313–320.
22. Leipzig RM, Cumming RG, Tinetti ME. Drugs and falls in older people: A systematic review and meta-analysis: I. Psychotropic drugs. J Am Geriatr Soc 1999;47:30.
23. Liu BA, Topper AK, Reeves RA, Gryfe C. Falls among older people: Relationship to medication use and orthostatic hypotension. J Am Geriatr Soc 1995;43: 1532–5415.
24. Ruthazer R, Lipsitz LA. Antidepressants and falls among elderly people in long-term care. Am J Public health 1993;83:746–749.
25. Thapa PB, Gideon P, Cost TW, et al. Antidepressants and the risk of falls among nursing home residents. N Engl J Med 1998;339:875–882.
26. Cumming RG. Epidemiology of medication-related falls and fractures in the elderly. Drugs Aging 1998;12:43–53.
27. Park-Lee E, Caffrey C, Sengupta M, et al. Residential care facilities: A key sector in the spectrum of long-term care providers in the United States. NCHS Data Brief 2011;78:1–8.
28. Gibson MJS, Andres RO, Kennedy TE, et al. Kellogg International Work Group on the Prevention of Falls by the Elderly. Kellogg International Program on Health and Aging. The prevention of falls in later life: A report of the Kellogg International Work Group on the Prevention of Falls by the Elderly. Medical Faculties of the Universities of Copenhagen and Aarhus, and the Danish National Board of Health; 1987.
29. Tromp A, Smit J, Deeg D, et al. Predictors for falls and fractures in the Longitudinal Aging Study Amsterdam. J Bone Miner Res 1998;13:1932–1939.
30. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: A 1-year prospective study. Arch Phys Med Rehabil 2001; 82:1050–1056.
31. Jasiewicz JM, Allum JHJ, Middleton JW, et al. Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal–cord injured individuals. Gait Posture 2006;24:502–509.
32. Cutlip RG, Mancinelli C, Huber F, DiPasquale J. Evaluation of an instrumented walkway for measurement of the kinematic parameters of gait. Gait Posture 2000;12:134–138.
33. McDonough AL, Batavia M, Chen FC, et al. The validity and reliability of the GAITRite system's measurements: A preliminary evaluation. Arch Phys Med Rehabil 2001;82:419–425.
34. Crum RM, Anthony JC, Bassett SS, Folstein MF. Population-based norms for the Mini-mental state examination by age and educational level. JAMA 1993;269: 2386–2391.
35. Shumway-Cook A, Horak FB. Assessing the influence of sensory interaction on balance. Phys Ther 1986;66:1548–1550.
36. Podsiadlo D, Richardson S. The Timed Up and Go: A test of basic functional mobility for frail elderly persons. J Am Geriatr Soc 1991;39:142–148.
37. Shumway-Cook A, Brauer S, Woollacott M. Predicting the probability for falls in community-dwelling older adults using the Timed Up and Go Test. Phys Ther 2000;80:896–903.
38. Simpson JM, Worsfold C, Reilly E, Nve N. A standard procedure for using TURN180: Testing dynamic postural stability among elderly people. Physiotherapy 2002;88:342–353.
39. Ebersbach G, MILAN RD, Poewe W. Influence of concurrent tasks on gait: A dual-task approach. Percept Motor Skills 1995;81:107–113.
40. Allum JHJ, Carpenter MG, Adkin AL. Balance control analysis as a method for screening and identifying balance deficits. Ann N Y Acad Sci 2001;942: 413–427.
41. Allum J, Carpenter M. A speedy solution for balance and gait analysis: Angular velocity measured at the centre of body mass. Curr Opin Neurol 2005;18:15.
42. Priest AW, Salamon KB, Hollman JH. Age-related differences in dual task walking: A cross-sectional study. J Neuro Eng Rehabil 2008;5:29.