

# Movement Path Tortuosity in Free Ambulation: Relationships to Age and Brain Disease

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**Abstract**—Ambulation is defined by duration, distance traversed, number and size of directional changes, and the interval separating successive movement episodes; more complex measures of ambulation can be created by aggregating these features. This review article of published findings defines random changes in direction during movement as “movement path tortuosity” and relates tortuosity to the understanding of cognitive impairments of persons of all ages. Path tortuosity is quantified by subjecting tracking data to fractal analysis, specifically Fractal Dimension (Fractal D), which ranges from a value of 1 when the movement path is perfectly straight to a value of 2 when the movement path is random, resembling the “drunkard’s walk.” The review elucidates the mathematical assumptions underlying Fractal D, its use in the analysis of movements of free ranging animals, and its application to the study of cognitive impairment and the prediction of falls in older adults. We conclude Fractal D offers a reliable, valid, sensitive, and easily interpreted real-time longitudinal measure of unrestricted movement path tortuosity unaffected by mobility aid use.

**Index Terms**—Animal behavior, cognition, fractals, mental disorders, numerical analysis, pervasive computing, ultra wideband technology.

## I. INTRODUCTION

AGE-RELATED slowing of upper and lower extremity movements is partly due to cognitive factors required for their execution. Age-related slowing of movements includes both quantitative and qualitative features of movement. Quantitative features are based on time to complete a task—speed of movement required to initiate or execute a movement. Historically, other observable features—hesitancies and directional changes during a single movement or variability among repetitive movements—are less studied, partly because they often are considered as errors in studies of movement speed and partly because quantitative analytic tools were unavailable.

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Age differences in cognition related to behavioral slowing present both as relatively longer total movement times in response to increasing task difficulty as well as the static perceptual-motor and variable decision making components of the reaction time [1], [2]. Qualitative movement features related to cognition are demonstrated by studies showing that changes in movement speed during pointing movement trajectories are greater in older persons [3]. Movement times as well as pointer placements in a repetitive tapping task are more variable in older age [4]. The coefficient of variation of an individual’s distribution of simple and forced choice reaction times increases with age in a variety of tasks [5]. Dykiert *et al.*’s review identified several studies showing that the age effect is relatively greater in patients with Parkinson’s disease and Alzheimer’s disease.

Slowing of lower extremity movements appears in reaction times and walking speed on predefined paths [3]; walking is slowed significantly when performing effortful cognitive tasks such as counting down by threes or monitoring an auditory channel for a predefined target [6]. Using short walking samples on a prescribed course, differences in gait sequencing have been observed [7] using very precise movement tracking tools. Older persons take a wider but shorter stride [8], [9] and show more stride to stride variability [10]. As with upper extremity movements, the age differences in normal aging are exaggerated in older persons with dementia.

The age differences in movement summarized above-employed methods restricting the degree to which movement could vary qualitatively, e.g., 6–8-m gait mats for walking, or visually defined targets for upper extremity movements. Except for reports using the coefficient of variation in speed of repeated responses [5], [11], methods to study direction changes or hesitancies in a path have lacked novel approaches. Readily observable changes in path direction that occur in dementia-related wandering, the staggering of the inebriate, or the “punch drunk” boxer, requires new methods of observation and quantification. Police employ field sobriety tests to determine how well inebriated drivers “can walk a straight line” and in the case of wandering behavior in dementia, Algase *et al.* [12], [13] have devised rating systems for trained observers that distinguish purposeful versus wandering movements, with the latter subdivided into random, pacing, and lapping. Among the subdivisions, the determination of “random” has proved the most difficult for human observers to recognize reliably, probably because humans are well suited to detecting periodic events (lapping and pacing) but not estimating how random one pattern of walking is compared to another.

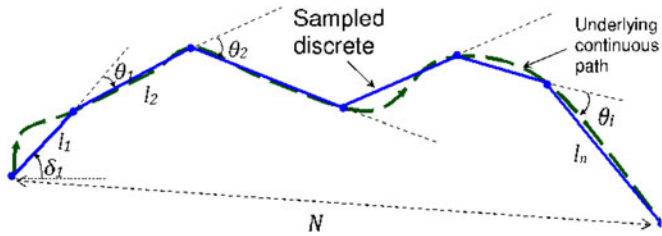


Fig. 1. Illustration of discretized sampling (solid line) of an underlying continuous movement path (dashed line), showing the various parameters of the sampled path. There are  $n$  steps in the path, the length and angle of step  $i$  are  $l_i$  and  $\delta_i$ , and the angle between steps  $i - 1$  and  $i$  is  $\theta_i$ . Path net displacement is  $N$ .

Recent developments in both indoor and outdoor movement tracking technologies have increased the opportunity to measure qualitative and quantitative features of unrestricted movements. The remainder of this paper describes: 1) the derivation and applications of a measure of movement path tortuosity called Fractal Dimension (Fractal D); 2) studies of age-associated differences in human movement using modified procedures developed by animal ecologists to study exploratory and food seeking behaviors; 3) summarizes results of several studies describing age-related changes in path variability to cognitive functioning and the prediction of future falls; and 4) discusses directions for future research.

## II. MEASURING MOVEMENT PATH TORTUOSITY

There is a long history of ecologists measuring the tortuosity of movement paths, mostly to measure foraging intensity. Typically, animals travel with continuous movement paths that we discretize by sampling at fixed time intervals (see Fig. 1). Thus, we are representing a continuous function as a discrete one. The discretization is both easy to visualize and is mathematically tractable. If we start sampling at location  $(x_0, y_0)$ , then the animal visits location  $(x_i, y_i)$  after  $i$  steps.

The length of step  $i$ ,  $l_i$ , is the distance from location  $i$  to  $i + 1$ , and the angle of step  $i$ ,  $\delta_i$ , is the angle between step  $i$  and horizontal. The turn angle is the angle between steps  $i - 1$  and  $i$ :

$$\theta_i = \delta_i - \delta_{i-1}. \quad (1)$$

The simplest earliest measure of tortuosity involves tracking the animal for a fixed distance and then measuring a “straightness index” [14]. Straightness compares the overall net displacement  $N$  of a path with  $n$  steps and total path length  $L$  and is given by

$$St = \frac{N}{L} = \frac{\sqrt{(x_n - x_0)^2 + (y_n - y_0)^2}}{\sum_{i=1}^n l_i} \quad (2)$$

$$\text{with } St \in [0, 1]. \quad (3)$$

Straightness is 0 when the animal returns to its starting point and is 1 when the path is completely straight. This measure is intuitively appealing because it has a range from 0 to 1 and is easy to calculate. There have been various other tortuosity indices proposed that are variations on Straightness [15]. The

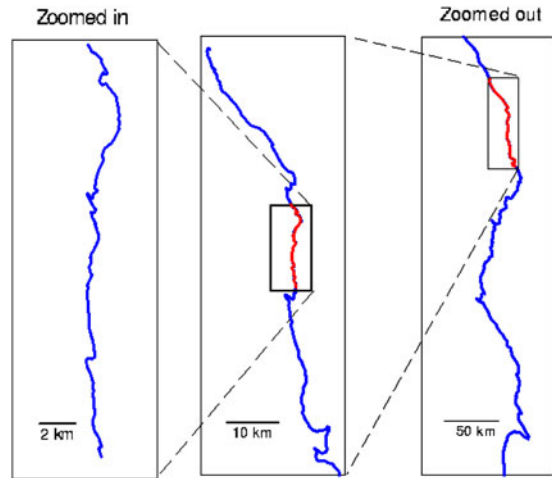


Fig. 2. Section of the coastline of Britain, viewed at three different spatial scales. Note that tortuosity is similar at all scales—i.e., the coastline is a fractal.

main problem with all of them is that they are affected by spatial scale in ways that are not always obvious [16]. Thus, a measure is needed that incorporates scale explicitly.

One tortuosity measure that incorporates scale explicitly was first proposed by Mandelbrot [17], who posed the question: What is the length of coastline of Britain? The answer is that it depends on the scale of measure. But more importantly, at each scale, the coastline looks similar. For example, Fig. 2 shows a section of the coastline of Britain at three spatial scales.

If you do not know the actual scales, it is difficult to tell which is the zoomed-in versus zoomed-out version simply by looking at the patterns. Thus, while the three maps do look different, all three have a similar geometrical pattern—the coastline shape is self-similar. Mandelbrot [17] introduced the term “fractal”; a geometrical shape is fractal if it has a similar pattern over a wide range of spatial scales. The map of the coastline of Britain is scale-free. We see examples of fractals in many other places in nature—for example, many species of fern leaves, and the branching in our lungs, show similar patterns at different spatial scales [18].

We can measure this pattern using the statistic “fractal dimension.” Strictly, fractal refers to a mathematical series in which the Hausdorff–Besicovitch dimension, or fractal, exceeds the Euclidean dimension [19], but “Fractal D” has a nice intuitive explanation—it is the continuous analogue to geometrical dimensions. For example, a straight line has a dimension of 1, and a plane has a dimension of 2. Lines have fractal dimensions ranging from 1 to 2, where at 1 they are completely straight and at 2 they are so tortuous as to completely cover the surface. The coastlines in Fig. 2 have a fractal dimension of 1.04, 1.05, and 1.05.

We can extend this idea to measuring the tortuosity of animal movement paths [19]. We estimate Fractal D, by measuring the gross path length at different scales,  $s$ . At each scale, length  $L(s)$  is measured by walking a pair of dividers along the map. Then, solving for  $D$  in the following equation:

$$L(s) = cs^{1-D} \quad (4)$$

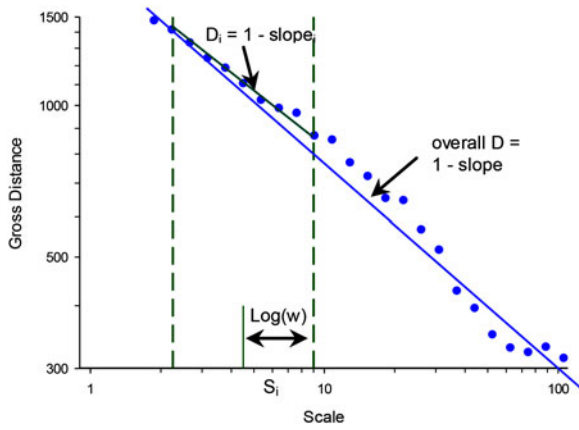


Fig. 3. The dots show Fractal  $D$  estimation. The vertical bars show Fractal  $D$  estimation over a range of scales centered at  $s_i$ , with a width of  $2 \text{Log}(w)$ .

where  $c$  is some constant of proportionality (see Fig. 3, circular symbols). Taking  $s$  to the power of  $1 - D$  instead of  $D$  allows  $D$  to be interpreted as the continuous analog to geometrical dimensions.

### A. Ecological Basis for Fractal $D$

Animal ecologists have developed conceptual models about how animals travel, which help us to understand how humans' cognition might affect their movement paths. We will first consider the simplest form of movement and then add in two layers of realism. At each stage, we will also discuss how this applies to the movement of people. These sections highlight how behavior varies with spatial scale and thus describing movements without considering spatial scale is dangerous.

### B. Aimless Wandering

There are three parts to the simplest form of movement. First, animals have a natural gait that determines how fast they travel, how much they turn, and how long each step is. Second, animals have a directional inertia, in that they tend to continue traveling in the direction they have been going in the past. Finally, when animals do turn, the direction and amount that they turn is not affected by any previous movement—there is a random component to it [20]. Intuitively, this is what one imagines as being “aimless wandering.”

We represent such movement paths mathematically, as follows. Move lengths and turning angles are distributed with probability distributions  $p(l)$  and  $g(\theta)$ . If movements are a series of independent, random draws, from the  $p(l)$  and  $g(\theta)$ , then the animal is traveling with a correlated random walk (CRW). The term “correlated” denotes that the  $\delta_i$  are correlated with each other, while the  $\theta_i$  are not. This means that the animal tends to walk in the same direction as it did in the past, but that at each step the turning angle is independent of the previous step length and angle. It is important to consider how CRWs are fractal. We do this by considering how straightness varies with total number

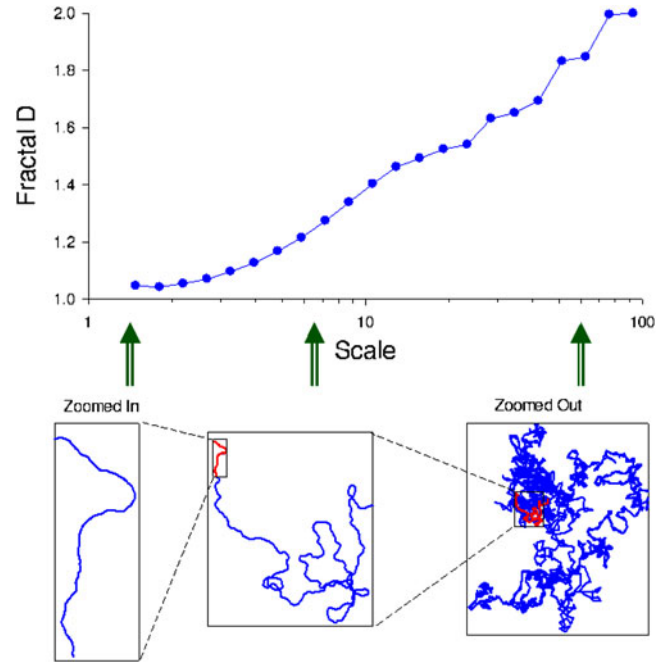


Fig. 4. Idealized animal traveling with a CRW. The top plot shows Fractal  $D$  as a function of spatial scale. Note that path tortuosity increases at larger scales. The bottom plots show the movement paths viewed at three specific different spatial scales.

of steps. It can be shown that

$$E(N) = k\sqrt{n} \quad (5)$$

for some constant  $k$  [21], [22]. Thus, since

$$L = \sum_{i=1}^n l_i = n\bar{l} \quad (6)$$

therefore

$$St \propto \frac{1}{\sqrt{n}}. \quad (7)$$

Thus, path Straightness depends on the number of steps. Furthermore, since

$$\lim_{n \rightarrow \infty} (St) = 0 \quad (8)$$

therefore path Straightness is 0 at very large scales. This means that as spatial scale increases, path tortuosity increases for CRW. Thus, CRWs are not self-similar.

One can understand this increase in path tortuosity intuitively as follows (see Fig. 3). At smaller spatial scales, the shape of a movement path is primarily determined by the animal's gait and thus is usually quite straight. It is more tortuous if the steps are shorter, if the animal is travelling slower, and if it is heavier. But at larger scales, the random turning effect increases and adds to the gait effect, causing path tortuosity to increase. Thus, as we zoom out, the path becomes more and more tortuous, until at large scales it is a completely random walk [23], [24] (see Fig. 4).

Overlaid on top of this is that animals need to avoid obstacles, which occur at various spatial scales. Thus, there is an added component to tortuosity that depends on the habitat. Imagine an inebriated person staggering down the street. At a small scale,

the person turns a bit at each step. But at larger scales, the person goes here and there with no seeming pattern.

This increase of tortuosity with scale at first glance seems contrary to the idea of Fractal D, since D was originally defined only for self-similar geometrical structures. However, we can adapt the idea of Fractal D to nonself-similar structures by estimating D as a function of scale, as follows. Choose  $m$  discrete values of scale,  $s_i$ , for  $i = 1 \dots m$ , such that  $\text{Log}[s_i]$  are equally spaced.  $D_i$  is the estimate of Fractal D for  $s_i$ . For each  $s_i$ , apply (4), solving for  $D_i$ , to give

$$D_i = 1 + \frac{\log(c_i) - \log(L_i(s))}{\log(s)} \quad (9)$$

but only over the range of scales from  $\frac{s_i}{w}$  to  $s_i w$ , for fixed values of  $w$ . Effectively, this uses a sliding window of fixed width  $2 \text{Log}(w)$  on the  $\text{Log}(\text{scale})$  axis to estimate D as a function of  $s$  (see Fig. 3, vertical bars).

There are some potential sampling issues caused by  $D$  being a function of scale. First, D estimates may be affected by the placement of the first step of the dividers. However, simulations show that the estimates for  $D_i$  are slightly improved by walking the dividers both forward and backward along the path, and using the mean of those two estimates, but that there is no benefit to starting the sampling at other places in the path [25]. Second, experiments must be designed to ensure that spatial scale is held constant across all treatments.

### C. Directed Movement

However, animals rarely travel aimlessly. Typically, they are traveling with some intent; they are going toward some place. For example, wolves regularly patrol their territory boundaries, marking them with urine [26] and zebras travel from one waterhole to another during the dry season [27]. People also usually travel with directed movement—you are going somewhere when you are walking. Thus, we will define directed walks as moving toward a known goal.

What does the movement path of directed travel look like? You might expect to see a completely straight path, but in the wild, this rarely happens. Consider this example. Suppose some wild animal wants to go to its home den. On the way there, it may have to go around a pond. But on the way to the pond, it may have to go around a thick clump of trees. And on the way to the clump of trees, it may have to go around a large deadfall. And on the way to the deadfall, it may have to go around individual trees or bushes. Thus, at each spatial scale, there are obstacles that it needs to go around, even though it is traveling in a directed manner. This can be modeled as follows. Suppose the start and end points of a path are  $(x_0, y_0)$  and  $(x_n, y_n)$ , and the distance and angle between the points are  $d_{0n}$  and  $\gamma_{0n}$ . Then, the middle coordinate would formed by

$$\begin{aligned} (x_{\frac{n}{2}}, y_{\frac{n}{2}}) &= (x_0 + d_{0n} (m_x \cos(\gamma_{0n}) - m_y \sin(\gamma_{0n})), \\ y_0 + d_{0n} (m_y \cos(\gamma_{0n}) + m_x \sin(\gamma_{0n}))) \end{aligned} \quad (10)$$

with  $(m_x, m_y)$  randomly drawn from some probability distribution  $h$ , with  $m_x \in (0, 1)$  and  $m_y \in (-\infty, \infty)$ —i.e.,  $m_x$  determines how far along the line segment you move between the

two points and  $m_y$  determines how far you vary orthogonally to this line segment. Then, the coordinates between  $(x_0, y_0)$  and  $(x_{\frac{n}{2}}, y_{\frac{n}{2}})$ , and  $(x_{\frac{n}{2}}, y_{\frac{n}{2}})$  and  $(x_n, y_n)$  would be chosen similarly, using the same probability distribution for  $(m_x, m_y)$ . This would be repeated for each pair of location coordinates. The structure of the habitat would determine the tortuosity of the movement path. Since natural landscapes are often self-similar over a wide ranges of scales [28], [29], directed paths such as this are fractal [30].

Consider an example with people. If you were walking across an open field, then your path would be quite straight. But if you are going from your home to your office, then, although you might be taking the straightest path possible, at a large scale, your path is constrained by the patterns of streets, and on a small scale, your path is constrained by the arrangements of rooms inside buildings. Directed paths look more like the coast of Britain than like aimless wandering.

### D. Perceptual Range

One last level of added realism is that animals can only see a limited distance around them—they have a certain perceptual range [31]. Animals' perceptual range can be visual [31], [32], olfactory [33], or auditory [34]. Furthermore, perceptual range is not limited to what animals can immediately perceive—animals form memory maps [35], and thus, more generally, perceptual range is the distance that animals can perceive their world, whether immediately or in memory.

How does perceptual range affect movement paths? It creates a threshold effect: at scales smaller than the perceptual range, paths are quite straight, but at scales larger than the perceptual range, paths are more tortuous [36]. Thus, decreasing the perceptual range makes paths more tortuous [37]. This effect can be used to test whether a movement path is directed—directed movement paths should travel further than a CRW at larger spatial scales [27].

At first glance, the idea of perceptual range might not seem relevant to people—although we can only see a limited distance around us, typically, we know the surrounding areas in our day-to-day travel. If we travel to our office, we know the route and the obstacles on the way. Thus, most of our movements seem to be inside the bounds of our perceptual range.

However, perceptual range is also temporal, not just spatial. In your mind, you plan your movements a certain time ahead. For example, although you may have a general idea of what you will be doing after supper, you may wait till you finish supper to decide exactly where to move to—whether to travel to the bathroom, or the TV room, or out somewhere. Or, even if you have decided what you will do after supper, your movement path still has an extreme change in direction at the supper table. Thus, practically, we travel both within and outside of our bounds of perceptual range.

### E. Combining It All

We can combine the ideas of directed movement, perceptual range, and aimless wandering for a more realistic view of how animals (and people) travel—and for an understanding of how



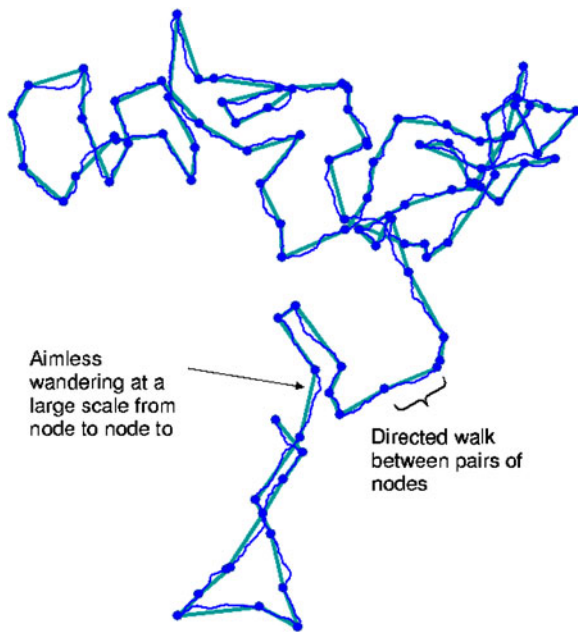


Fig. 5. Movement path of an animal traveling in a directed manner between nodes, but revealing aimless wandering (CRW) on a large scale.

dementia can affect the movement of people. An animal decides where to travel based on its perceptual range. It goes there in directed travel. Then, at that node, it decides anew where to go. This creates directed travel on a small scale between nodes, but aimless wandering at a large scale from node to node (see Fig. 5). For example, wood mice travel in quite straight patterns on a small scale from one shrub to another, but travel with aimless wandering on a large scale between shrubs [38].

Consider the travel of a resident of a nursing home or assisted living facility (ALF), throughout a day. Their nodes might be their bedroom, the bathroom, the dining room, and a commons area. On a small scale, their path between those is inherently straight, but constrained by furniture and the arrangements of the rooms. But at a large scale, their path from one node to the other is quite tortuous, as at each node, they decide where to travel again.

But then suppose someone is walking from one room to another and becomes confused, not sure where they were going. Conceptually, their temporal perceptual range has suddenly decreased. They might turn and go in a different direction than they had been going, adding a node in their path—i.e., the distances between nodes would decrease, causing path tortuosity to increase. Thus, we would expect that Fractal D of movement paths would increase with the onset of dementia. Thus, although Fractal D does vary with spatial scale, we expect that Fractal D will increase overall.

### III. FRACTAL D IN RELATION TO AGING AND BRAIN DISEASE

Our motive for relating movement path tortuosity to age-associated cognitive deficits was driven by a need to develop an operational definition of the random elements of wandering. Algase *et al.* [13] identified 23 different definitions of

dementia-related wandering; the common feature among all definitions was apparently aimless ambulation that proved difficult for observers to quantify. In the landmark study of Algase *et al.* [12], trained observers were able to identify purposeful walking, lapping, and pacing, and somewhat by a process of elimination, what they termed random ambulation.

Since humans clearly were unable to definitively observe and quantify “random” movement, we sought a mechanical observer that could gather data continuously on many elders for months at a time and not suffer observer fatigue while measuring small directional changes in unrestricted ambulation of as many as 100 persons at once. We selected the Ubsense (Ubsense, LLC, Cambridge, U.K.) Ultrawideband Real Time Location System (UWB-RTLS) system. Elders wore a small wrist transponder whose position was triangulated by four sensors, which yielded 3-D positioning relative to an arbitrary origin in the corner of a  $9 \times 15$  m lobby of an ALF. The spatial resolution of the transponder was 20 cm in all three axes, and the sampling rate was 0.43 s. X, Y, and Z coordinate data were written to a database in near real time for all tags. The accuracy of the system was determined in a published pilot investigation [39] and the accuracy of the UWB-RTLS tracking data was compared against a Vicon, Inc., system employed in kinematic studies.

To compute tortuosity from the raw tracking data, we initially adopted the published procedures of Nams [24], but in later work, Fractal D was calculated automatically using a Real-Time Fractal Path Analysis algorithm developed by Craighead [40]. A path was defined as a period of movement bounded by 60s of immobility of the transponder. In addition to each path’s tortuosity index, the duration and distance of the movement and walking speed during the path were calculated. The estimates are aggregated as needed for the project in question, usually over 24 h.

Since Fractal D does vary with scale, yet we are estimating one overall Fractal D value, it is important that studies be designed so results do not depend on spatial scales used. We ensured this in three ways: First, we estimated one D-value over a wide range of scales [e.g., using (4)]. Second, the ranges of scales were wide enough to cover all of the potentially interesting behaviors—from below step size to the limits set by the size of the buildings. Finally, in each experiment, we used the same range for all treatments.

The particular algorithm we used to estimate D varied among studies because of differences in our intent. Initially, we were testing whether path tortuosity can be used to measure cognitive impairment. We set specific scales and then estimated D-values from the whole dataset after the end of sampling. But in later studies, we were testing the applicability of this approach to real-world situations. For this technique to be useful, we need continuously updated predictions of cognitive impairment. We cannot wait till the end of all the sampling to estimate path tortuosity. Thus, we used an algorithm that automatically sets the range of scales from  $\frac{1}{2}$  of step size to  $10\times$  the step size and gives continuously updated estimates of Fractal D [40].

All published human subjects research conducted by Kearns *et al.* and presented hereafter was approved by Institutional Review Board of the University of South Florida. Kearns *et al.*

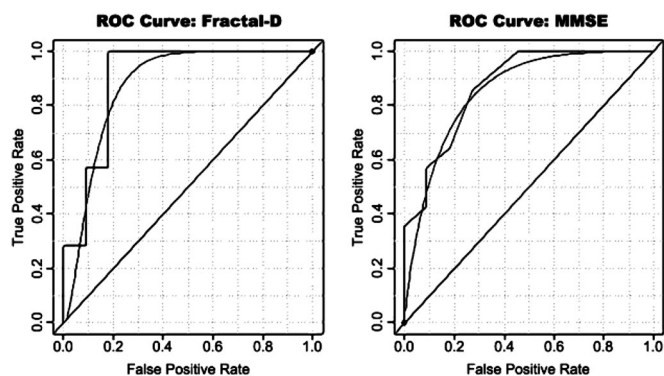


Fig. 6. Classification of persons with clinical diagnosis of dementia using Fractal Dimension versus the MMSE.

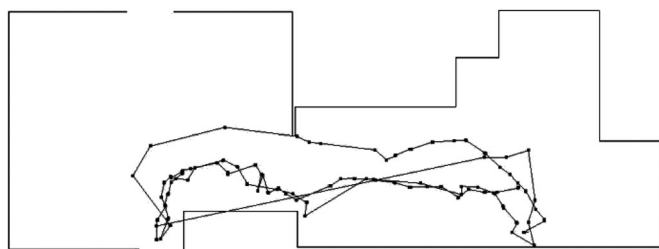


Fig. 7. Paths of Subject 1, a woman with an MMSE of 25 (normal cognition) and a Fractal D of 1.2. Note the linearity of the paths across the lobby space.

[41] evaluated movement path tortuosity in 14 elderly ALF residents for 30 days as residents passed through an instrumented lobby separating bedroom, functional, and dining areas. Consenting participants were administered the Mini Mental State Exam (MMSE) [42] by a trained examiner. The MMSE is a widely used 30 item test for cognitive impairment, used by clinicians and researchers studying older adults to evaluate deficits in short term memory, temporal and spatial orientation, ability to follow commands, attention, language, and calculation and registration. The test results are frequently used to help determine a diagnosis of dementia. The main finding was a statistically significant  $-0.47$  correlation between Fractal D and MMSE; greater path tortuosity predicted lower MMSE scores (poorer cognitive performance). The study was replicated on a larger sample of 25 residents across two ALFs [43], which included residents with a clinical diagnoses of dementia. An unexpected finding was that Fractal D was considerably better at classifying persons with a dementia diagnosis; two misclassifications, compared to six for the MMSE (see Fig. 6).

The relationship between path tortuosity and cognitive impairment is shown in another way in Figs. 7 and 8, which shows a representation of the paths generated by two residents of one ALF over the same 2-h period as they walked through the monitored lobby, passing from the dormitory to the dining area, which also housed a medication dispensing station and staff offices.

It is possible that the movements of the participant with high Fractal D reflect many stops made for social interactions. One indirect approach to evaluating this hypothesis would be to measure the number of tag-wearing residents who were in close

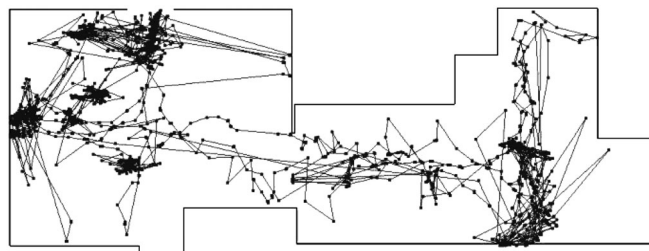


Fig. 8. Paths of Subject 2, a woman with an MMSE score of 21 indicating cognitive impairment and a Fractal D of 1.40.

proximity to or in tandem movement with the participant. This was not possible because only a subset of residents occupying the space wore transponders.

A subsequent published study of 53 ALF residents by Kearns *et al.* [44] examined tortuosity in the week before the resident fell. Using logistic regression, we found high tortuosity (higher Fractal D) and the presence of a fall in the prior year yielded an 80% correct classification of faller status. An attempt at a three-factor model incorporating walking speed, Fractal D, and past fall history failed, with walking speed's influence eclipsed by Fractal D. The results clearly indicated that walking tortuous paths (having a “drunkard’s walk”) was a risk factor for future falls and confirmed that the best long-term predictor of future falls was having a prior fall. Moreover, the results also showed that Fractal D was a dynamic measure, subject to change over periods of days if not hours. The relationship between Fractal D and future falls decayed as a function of time with “stale” readings (those older than a week) having little prognostic value. The underlying neurological mechanisms determining Fractal D deserve attention, and these likely include executive function, spatial orientation, vision, and balance.

Traumatic brain injuries provide additional evidence for the significance of temporal variability in Fractal D. Kearns *et al.* [45] gathered mean daily Fractal D on 22 veterans over their months-long rehabilitation in a residential polytrauma facility. Ten patients had discernable declines in Fractal D during their residency, while 12 did not. Independent clinicians judged those with declining trends to have significantly better clinical outcomes on the Mayo Portland Adaptability Index, the facility’s primary assessment tool. Thus, long-term changes in Fractal D may serve as a useful adjunct to clinical care for persons with head trauma, potentially alerting clinicians to unanticipated reversals in progress and facilitating the staging of treatments.

A later study with veterans in the same residential polytrauma facility [46] found Fractal D at admission predicted their ability to successfully perform prompted behaviors during months of subsequent therapy for TBI. Prompts to attend scheduled appointments and take medications while observed at the nurses’ station were delivered to the veteran via the nearest of 30 wall-mounted displays. A behavior occurring within a half hour of a prompt was deemed successful. Success was verified by the location tracking data that indicated the veteran appeared at the locations specified. More than 60% of responses occurred within 15 min of delivery of the first prompt.

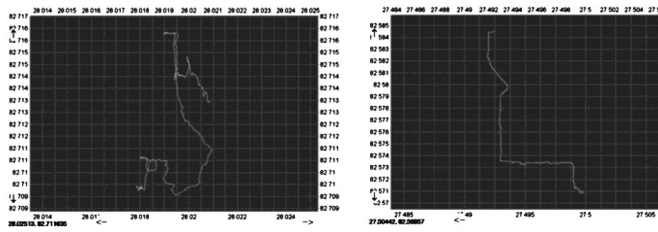


Fig. 9. (Left) GPS track of a traumatic brain injury victim with Fractal D of 1.37. (Right) Normal subject with a Fractal D of 1.11.

In the study just described, the Fractal D at admission was derived from data from a GPS logger worn in a shirt pocket by the veteran during a single self-determined half-hour walk outdoors. The veteran was allowed to determine the course, while an attending research assistant prevented the veteran from coming to harm. The latitude and longitude were read each second to a spatial resolution of approximately 2.5 m, and the successful compliance with prompts was accomplished using data from the indoor movement tracking system previously described [47]. The validity of the Fractal D assessments using the GPS logger was determined in an earlier study comparing the outdoor ambulation of two groups of community veterans: one with a history of TBI and a comparable group of veterans without TBI [48]. Veterans in the TBI group had incurred injuries while in military service up to 10 years earlier. Successfully measuring Fractal D with two somewhat different systems provided an increased degree of confidence that the assessment method was robust and not simply an artifact of the chosen method of measurement (see Fig. 9).

#### IV. DISCUSSION

##### A. Movement Tracking of Unrestricted Movements and in Conditioning

In ecological studies, Fractal D quantifies spatial variability of animal movements along a continuum from extremely random, with values approaching 2 for movements characterizing exploratory activities such as locating food and mates, to highly goal-directed movements, involving nearly straight line travel with values approaching 1 that an animal might take to gain the safety of a burrow when foraging is complete. During goal-directed movements, high Fractal D values may occur when changes in path direction are necessary to circumnavigate environmental barriers. Cognition is not usually studied as an independent factor in ecological studies; poor cognitive abilities in an animal typically result in an animal falling prey, and being removed from the gene pool. While studies of maturation to adulthood in wild animals do exist, movement path tortuosity has, to our knowledge, not been employed in the study of aging in wild animals.

In contrast, studies of animal and human conditioning and learning have focused on the conditions that influence how well or how fast the target behavior is isolated from the repertoire of behaviors of the learner. In operant conditioning studies, the process of “magazine training” involves pairing the sound of the electromechanical feeder with the delivery of a food pellet so that the pellet’s delivery may be used to reinforce some novel

behavior [49]. A very hungry subject is introduced to the new environment and begins an aggressive search for food (Fractal D is high), which continues until the first food pellet is delivered. After delivery of the first reinforcer, competing nonproductive responses are progressively eliminated as the subject takes a progressively straighter line to the magazine (yielding lower Fractal D—more goal directed behavior). Once magazine training is complete, the “method of successive approximations to a goal” (aka Shaping) is used to train the subject to manipulate the response lever on its own, thereby allowing it to deliver food reinforcers autonomously. During shaping, the subject may generate more search behavior and competing responses (resulting in a higher Fractal D) as it attempts, through trial and error, to make its behavior conform to the new contingencies established by the experimenter. In this example, active search behaviors facilitate learning the new contingencies of reinforcement, but as they are learned, search behaviors (and higher Fractal D movement components) cease and are replaced by progressively more efficient responding (i.e., response lever pressing), which meets the new contingency with a minimum of wasted effort (and a return to lower Fractal D levels).

In alleyways or similar restricted test environments, an animal’s maximum running speed is often taken as an index of the effectiveness of the conditioning and is principally attributed to the elimination of competing responses such as hesitations while exploring the alleyway. While movement path tortuosity could, in principle, serve as a direct measure of the reduction of competing responses during alleyway conditioning, the choice of measures, details of scaling, and type of apparatus used would require specification. The strongest link between learning and environmental factors has been provided by studies concerning the role of distal and proximal visual cues in maze learning [50]. As in ecological studies, the independent assessment of cognitive abilities in animal learning is rarely conducted. In studies of aging’s impact on human learning and performance, independent assessments of cognitive factors required to successfully perform a task are common, particularly for tasks requiring sustained attention and attentional control [50]. We conclude from these observations that path tortuosity offers a direct method for exploring mechanisms underlying learning and skill acquisition.

The studies of humans summarized above have focused on the relationship between cognitive deficits and elevated movement path tortuosity in older persons with and without a clinical diagnosis of dementia, and young and middle-aged persons suffering TBI. In these studies, increased path tortuosity is attributed to a change in a highly overlearned performance as a result of both normal and pathological aging and brain disease. The longitudinal study showing decreasing Fractal D in veterans indicates recovery of cognitive functioning over the course of treatment is accompanied by a decline in Fractal D [45].

##### B. Path Tortuosity and Other Descriptive Schemes for Movement

The movement ecology paradigm [51] provides a broad conceptual framework for analyzing movements of both living and inanimate objects. The paradigm is built around three questions: why move; where to move; how to move. In both the



study of animals' movements in natural habitats and our human studies, the primary link between cognition and movement is where to move. In animal studies, the why and how questions are answered in terms of the distinction between random and directed movement. In human studies, greater path tortuosity is attributed to difficulty in choosing or maintaining a desired movement path resulting from spatial disorientation and certain failures of memory—sometimes referred to as executive function. A consistent finding in all of the human studies described was that differences in how the movement is accomplished do not alter Fractal D—the relation between cognitive deficit and Fractal D persists across persons using wheelchairs, walkers, or other mobility aids—elevated Fractal D results from difficulty in navigating a movement path rather than how it is traversed. In animal and human studies, the question of “why move” has been assumed to be a given—the issue is where to move in order to meet the goal of the movement. In very advanced cases of dementia seen in institutional settings, the person with dementia may require assistance in determining “why move” as well; (s)he eventually requires personal escorting to specific locations—bedroom, dining area, etc. [52].

### C. New Opportunities for Research and Intervention

While our research has shown that short-term increases in Fractal D are predictive of falls within the next seven days, the underpinnings of the elevation are not understood and limit the options for intervening. Of all the predictors evaluated in Kearns *et al.* [41], only a history of one or more falls in the prior year, a common finding in such research, contributed to future falls. Another hypothesized fall predictor was antipsychotic and antidepressant medication use, but that hypothesis was not supported; almost all participants were receiving one or more of those medications for the entire study period, so their adaptation or tolerance to the drug had long since been complete. We also examined the influence of other medications, particularly antibiotics, to treat short-term infections. Given that short-term cognitive impairment is linked to increased path tortuosity, we expected that painkiller and antibiotic use might be a mediating factor. We found suggestive but inconclusive evidence of a relationship between the timing of falls and the treatment of those infections.

An improvement in future studies of path-tortuosity-related falls would be to employ automated fall detectors to indicate precisely where and when they occurred. Only 51 of 71 staff-reported falls in our study met our definition of a movement-related fall. Our automatic measures of movement path tortuosity were gathered as participants traveled within a monitored lobby; yet almost all falls occurred in their private bed and bathroom areas and were inferred from staff-generated “incident reports,” which often contained only information about the fall provided by the faller.

In addition to measuring short-term path tortuosity changes predictive of future falls, Fractal D may be useful for evaluating the long-term consequences of a fall or the all too common concussion in contact sports. Our research to date has identified long-term effects of TBI on Fractal D as well as documented changes in the measure over the course of TBI rehabilitation.

## V. CONCLUSION

The main goal of the research summarized by this review was to create an additional tool for describing the relationships between cognitive changes in aging and/or brain disease and human ambulation. The added value of the tool, called Fractal D, to existing procedures for studying speed of human ambulation is that it provides a direct measure of the spatial variability of ambulation. Fractal D deals with the geometry of lines and as employed here is used to study changes in path direction. The present application of Fractal D measures spatial variability of multiple free-ranging individuals simultaneously over extended periods indoors to address primary research questions relating movement path tortuosity changes to cognitive declines in middle aged and elderly persons, some with dementia and some with traumatic brain injury. In each of these areas, Fractal D has augmented earlier research findings by elucidating the severity and trajectory of cognitive deficit as recovery occurs over successive episodes of rehabilitation. Elevated Fractal D is also a potent predictor of movement-related falls in the elderly.

Fractal D has been employed by animal ecologists to describe exploratory and directed movements of animals in their natural environments. The present essay reviews and summarizes some of that seminal work and describes its adaptation to the study of voluntary human ambulation. Several areas of research and clinical intervention were described.

## REFERENCES

- [1] R. T. Anders and J. L. Fozard, “Effects of age upon retrieval from primary and secondary memory,” *Develop. Psychol.*, vol. 9, pp. 411–415, 1973.
- [2] D. J. Madden, “Speed and timing of behavioural processes,” in *The Handbook of the Psychology of Aging*, J. D. Birren and K. W. Schaie, Eds. Burlington, MA, USA: Elsevier, 2001, pp. 288–312.
- [3] C. J. Ketcham and G. E. Stelmach, “Age-related declines in motor control,” in *The Handbook of the Psychology of Aging*, J. D. Birren and K. W. Schaie, Eds. Burlington, MA, USA: Elsevier, 2001, pp. 313–348.
- [4] A. T. Welford, A. H. Norris, and N. W. Shock, “Speed and accuracy of movement and their changes with age,” *Acta Psychologica*, vol. 30, pp. 3–15, 1969.
- [5] D. Dykiert, G. Der, J. M. Starr, and I. J. Deary, “Age differences in intra-individual variability in simple and choice reaction time: Systematic review and meta-analysis,” *PLoS One*, vol. 7, no. 10, p. e45759, 2012.
- [6] A. Ble, S. Volpato, G. Zuliani, J. M. Guralnik, S. Bandinelli, F. Lauretani, B. Bartali, C. Maraldi, R. Fellin, and L. Ferrucci, “Executive function correlates with walking speed in older persons: The InCHIANTI study,” *J. Am. Geriatr. Soc.*, vol. 53, no. 3, pp. 410–415, 2005.
- [7] B. Najafi, K. Aminian, A. Paraschiv-Ionescu, F. Loew, C. J. Bula, and P. Robert, “Ambulatory system for human motion analysis using a kinematic sensor: Monitoring of daily physical activity in the elderly,” *IEEE Trans. Bio-Med. Eng.*, vol. 50, no. 6, pp. 711–723, Jun. 2003.
- [8] J. M. Hausdorff, G. Yogev, S. Springer, E. S. Simon, and N. Giladi, “Walking is more like catching than tapping: Gait in the elderly as a complex cognitive task,” *Exp. Brain Res.*, vol. 164, no. 4, pp. 541–548, 2005.
- [9] G. Yogev, N. Giladi, C. Peretz, S. Springer, E. S. Simon, and J. M. Hausdorff, “Dual tasking, gait rhythmicity, and Parkinson’s disease: Which aspects of gait are attention demanding?” *Eur. J. Neurosci.*, vol. 22, no. 5, pp. 1248–1256, 2005.
- [10] T. Herman, N. Giladi, T. Gurevich, and J. M. Hausdorff, “Gait instability and fractal dynamics of older adults with a “cautious” gait: Why do certain older adults walk fearfully?” *Gait Posture*, vol. 21, no. 2, pp. 178–185, 2005.
- [11] J. M. Hausdorff, “Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking,” *Human Movement Sci.*, vol. 26, no. 4, pp. 555–589, 2007.



- [12] D. L. Algase, E. R. A. Beattie, J. A. Song, D. Milke, C. Duffield, and B. Cowan, "Validation of the Algase wandering scale (version 2) in a cross cultural sample," *Aging Mental Health*, vol. 8, no. 2, pp. 133–142, 2004.
- [13] D. Algase, D. Moore, C. Vandeweerd, and D. J. Gavin-Dreschnack, "Mapping the maze of terms and definitions in dementia-related wandering," *Aging Mental Health*, vol. 11, no. 6, pp. 686–698, 2007.
- [14] E. Batschelet, *Circular Statistics in Biology*. London, U.K.: Academic Press, 1981.
- [15] S. Benhamou, "How to reliably estimate the tortuosity of an animal's path: Straightness, sinuosity, or fractal dimension?" *J. Theor. Biol.*, vol. 229, no. 2, pp. 209–220, 2004.
- [16] E. A. Codling, M. J. Plank, and S. Benhamou, "Random walk models in biology," *J. Royal Soc. Interface*, vol. 5, no. 25, pp. 813–834, 2008.
- [17] B. Mandelbrot, "How long is the coast of Britain? Statistical self-similarity and fractional dimension," *Science*, vol. 156, pp. 636–638, 1967.
- [18] B. B. Mandelbrot, *The Fractal Geometry of Nature*. New York, NY, USA: Macmillan, 1983.
- [19] M. Dicke and P. A. Burrough, "Using fractal dimensions for characterizing the tortuosity of animal trails," *Physiol. Entomol.*, vol. 13, no. 4, pp. 393–398, 1988.
- [20] C. E. McCulloch and M. L. Cain, "Analyzing discrete movement data as a correlated random walk," *Ecology*, vol. 70, no. 2, pp. 383–388, 1989.
- [21] P. Bovet and S. Benhamou, "Spatial analysis of animals' movements using a correlated random walk model," *J. Theor. Biol.*, vol. 131, no. 4, pp. 419–433, 1988.
- [22] J. A. Byers, "Correlated random walk equations of animal dispersal resolved by simulation," *Ecology*, vol. 82, no. 6, pp. 1680–1690, 2001.
- [23] P. Turchin, "Fractal analyses of animal movement—A critique," *Ecology*, vol. 77, no. 7, pp. 2086–2090, 1996.
- [24] V. O. Nams, "Using animal movement paths to measure response to spatial scale," *Oecologia*, vol. 143, pp. 179–188, 2005.
- [25] V. O. Nams, "Improving accuracy and precision in estimating fractal dimension of animal movement paths," *Acta Biotheoretica*, vol. 54, pp. 1–11, 2006.
- [26] R. P. Peters and L. D. Mech, "Scent-marking in wolves: Radio-tracking of wolf packs has provided definite evidence that olfactory sign is used for territory maintenance and may serve for other forms of communication within the pack as well," *Amer. Sci.*, vol. 63, no. 6, pp. 628–637, 1975.
- [27] C. J. Brooks and S. Harris, "Directed movement and orientation across a large natural landscape by zebras, *Equus burchelli antiquorum*," *Animal Behaviour*, vol. 76, no. 2, pp. 277–285, 2008.
- [28] J. R. Krummel, G. Gardner, G. Sugihara, R. V. Oneill, and P. R. Coleman, "Landscape patterns in a disturbed environment," *Oikos*, vol. 48, pp. 321–4, 1987.
- [29] R. V. Sole and S. V. Manrubia, "Are rainforests self-organized in a critical state?" *J. Theor. Biol.*, vol. 173, no. 1, pp. 31–40, 1995.
- [30] V. O. Nams, "Detecting oriented movement of animals," *Animal Behaviour*, vol. 72, no. 5, pp. 1197–1203, 2006.
- [31] P. A. Zollner and S. L. Lima, "Landscape-level perceptual abilities in white-footed mice: Perceptual range and the detection of forested habitat," *Oikos*, vol. 80, no. 1, pp. 51–60, 1997.
- [32] E. A. Gillis and V. O. Nams, "How red-backed voles find habitat patches," *Can. J. Zool.*, vol. 76, no. 5, pp. 791–794, 1998.
- [33] R. L. Schooley and L. C. Branch, "Limited perceptual range and anemotaxis in marsh rice rats *Oryzomys palustris*," *Acta Theriologica*, vol. 50, no. 1, pp. 59–66, 2005.
- [34] M. C. Wells and M. Bekoff, "Predation by wild coyotes: Behavioral and ecological analyses," *J. Mammal.*, vol. 63, no. 1, pp. 118–127, 1982.
- [35] A. O. Gautesstad and I. Mysterud, "Complex animal distribution and abundance from memory-dependent kinetics," *Ecol. Complexity*, vol. 3, no. 1, pp. 44–55, 2006.
- [36] J. A. Prevedello, G. Forero-Medina, and M. V. Vieira, "Movement behaviour within and beyond perceptual ranges in three small mammals: Effects of matrix type and body mass," *J. Animal Ecol.*, vol. 79, no. 6, pp. 1315–1323, 2010.
- [37] G. Pe'er and S. Kramer-Schadt, "Incorporating the perceptual range of animals into connectivity models," *Ecol. Model.*, vol. 213, no. 1, pp. 73–85, 2008.
- [38] S. Benhamou, "An analysis of movements of the wood mouse *Apodemus sylvaticus* in its home range," *Behavioural Process.*, vol. 22, no. 3, pp. 235–250, 1990.
- [39] W. Kearns, D. Algase, D. Moore, and S. Ahmed, "Ultra wideband radio: A novel method for measuring wandering in persons with dementia," *Gerontechnology*, vol. 7, no. 1, pp. 48–57, 2008.
- [40] J. Craighead, "Using fractal dimension to assess robot operator search skill," presented at the IEEE Int. Workshop Safety, Security Rescue Robot., Denver, CO, USA, Nov. 3–6, 2009.
- [41] W. D. Kearns, V. O. Nams, and J. L. Fozard, "Tortuosity in movement paths is related to cognitive impairment. Wireless fractal estimation in assisted living facility residents," *Methods Inf. Med.*, vol. 49, no. 6, pp. 592–598, 2010.
- [42] R. M. Crum, J. C. Anthony, S. S. Bassett, M. F. Folstein, "Population-based norms for the mini-mental state examination by age and educational level," *JAMA*, vol. 269, no. 18, pp. 2386–2391, 1993.
- [43] W. Kearns, J. L. Fozard, V. O. Nams, and J. D. Craighead, "Wireless telesurveillance system for detecting dementia," *Gerontechnology*, vol. 10, pp. 90–102, 2011.
- [44] W. D. Kearns, J. L. Fozard, M. Becker, J. M. Jasiewicz, J. D. Craighead, L. Holtsclaw, and C. Dion, "Path tortuosity in everyday movements of elderly persons increases fall prediction beyond knowledge of fall history, medication use, and standardized gait and balance assessments," *J. Amer. Med. Directors Assoc.*, vol. 13, no. 7, pp. 665.eC7–665.e13, 2012.
- [45] W. D. Kearns, S. Scott, J. Fozard, C. Dillahunt-Aspillaga, and J. Jasiewicz, "Decreased movement path tortuosity is associated with improved functional status in TBI patients," *J. Head Trauma Rehabil.*, vol. 31, pp. E13–E19, 2016.
- [46] W. D. Kearns, J. Fozard, R. Ray, S. Scott, J. Jasiewicz, J. Craighead, and C. V. Pagano, "Movement path tortuosity predicts compliance with therapeutic behavioral prompts in patients with traumatic brain injury," *J. Head Trauma Rehabil.*, vol. 31, no. 1, pp. E20–E27, 2016.
- [47] J. Jasiewicz, W. Kearns, J. Craighead, J. L. Fozard, S. Scott, and J. McCarthy, Jr., "Smart rehabilitation for the 21st century: The Tampa Smart Home for veterans with traumatic brain injury," *J. Rehabil. Res. Develop.*, vol. 48, no. 8, pp. vii–xviii, 2011.
- [48] W. D. Kearns, J. L. Fozard, L. Schonfeld, S. Scott, and K. Marshall, "Elevated movement path tortuosity in voluntary outdoor ambulation in community-dwelling veterans with a history of traumatic brain injury," *J. Head Trauma Rehabil.*, vol. 30, no. 1, pp. E8–E14, 2015.
- [49] C. Ferster and B. Skinner, *Schedules of Reinforcement*. Cambridge, MA, USA: B. F. Skinner Foundation, 1957.
- [50] W. A. Rogers and A. D. Fisk, "Understanding the role of attention in cognitive aging research," in *The Handbook of the Psychology of Aging*, J. D. Birren and K. W. Schaie, Eds. Burlington, MA, USA: Elsevier, pp. 267–287, 2001.
- [51] R. Nathan, W. M. Getz, E. Revilla, M. Holyoak, R. Kadmon, D. Saltz, and P. E. Smouse, "A movement ecology paradigm for unifying organismal movement research," in *Proc. Nat. Acad. Sci. USA*, vol. 105, no. 49, pp. 19052–19059, 2008.
- [52] N. L. Mace and P. V. Rabins, *The 36-Hour Day: A Family Guide to Caring for People Who Have Alzheimer's Disease, Related Dementias, and Memory Loss*, 5th ed. Baltimore, MD, USA: Johns Hopkins Univ. Press, 2011, xxiv, p. 353.



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