Published in final edited form as:
J Am Geriatr Soc. 2011 February ; 59(2): 345–352. doi:10.1111/j.1532-5415.2010.03267.x.

Cellular Telephones Measure Activity and Lifespace in Community-Dwelling Adults: Proof of Principle

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Abstract

OBJECTIVES—To describe a system that uses off-the-shelf sensor and telecommunication technologies to continuously measure individual lifespace and activity levels in a novel way.

DESIGN—Proof of concept involving three field trials of 30, 30, and 21 days.

SETTING—Omaha, Nebraska, metropolitan and surrounding rural region.

PARTICIPANTS—Three participants (48-year-old man, 33-year-old woman, and 27-year-old male), none with any functional limitations.

MEASUREMENTS—Cellular telephones were used to detect in-home position and in-community location and to measure physical activity. Within the home, cellular telephones and Bluetooth transmitters (beacons) were used to locate participants at room-level resolution. Outside the home, the same cellular telephones and global positioning system (GPS) technology were used to locate participants at a community-level resolution. Physical activity was simultaneously measured using the cellular telephone accelerometer.

RESULTS—This approach had face validity to measure activity and lifespace. More importantly, this system could measure the spatial and temporal organization of these metrics. For example, an individual's lifespace was automatically calculated across multiple time intervals. Behavioral time budgets showing how people allocate time to specific regions within the home were also automatically generated.

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Preliminary results from this study were presented at the 2010 AGS meeting, Orlando, Florida.

Conflict of Interest: The editor in chief has reviewed the conflict of interest checklist provided by the authors and has determined that the authors have no financial or any other kind of personal conflicts with this paper.

Author Contributions: Initial concepts and framework developed by SJB, AKS, and EHG. Software development by AKS, BCW, and EHG. Field testing of system by SJB, CAH, and RHC. Data analysis by SJB and AKS. Manuscript preparation by SJB, AKS, JFP. Start-up support and mentorship provided by JFP.

CONCLUSION—Mobile monitoring shows much promise as an easily deployed system to quantify activity and lifespace, important indicators of function, in community-dwelling adults.

Keywords

lifespace assessment; automated; actimetry; global positioning system; GPS; cellular phone; spatiotemporal organization of human behavior; time budget; automated; human

Older adults constitute growing percentages of the total population throughout the world.[1–4] Thus, a large and increasing proportion of total healthcare expenditures will be spent in care of older individuals. To ensure that healthcare resources are used as effectively as possible, it is essential for medical practitioners to have access to high-quality data that precisely measure the outcome of specific clinical interventions. For older, and specifically, frailer people with chronic medical and psychiatric limitations, the most important outcome is an individual's functional status.[5,6] Current measurements of functional status rely on self- or caregiver-provided status reports or brief physical performance batteries that cannot capture detailed patterns of daily behavior, yet daily patterns of behavior are a rich source of information regarding functioning and play an important role in quality of life. Unfortunately, daily patterns of function—how a person performs essential day-to-day tasks of living (including, but not limited to, mobility, locomotion, eating, drinking, dressing, bathing, toileting, housekeeping, and socializing)—are exceedingly difficult to measure in an ambulatory population.

An individual's specific strengths and limitations performing the above tasks are expressed as their enacted function.[7] Lifespace, a measure of the frequency, independence, and geographic extent of an individual's travels, has much face validity and is a particularly effective way to estimate enacted function.[8] Lifespace correlates with important health status outcomes, including observed physical performance,[9,10] nutritional risk,[11,12] clinical course after medical versus surgical hospitalization,[13] and metrics of self-reported functional capacity and affect.[14] Lifespace may also have prognostic value to identify individuals within a community most at risk for failure to thrive.[15]

Herein is provided a first description and proof of principle for a fundamentally new approach to measure patterns of activity and lifespace in community-dwelling individuals. Briefly, a system in which data measuring individual activity and lifespace is continuously collected is described. These data are quality controlled and classified to extract relevant behavioral features. Extended observations are made of the temporal and spatial patterns of an individual's activity and lifespace using inexpensive and ubiquitous electronic devices. These measurements minimally disrupt an individual's personal privacy and are easily collected. Behaviors are classified in a manner analogous to prior work studying home cage behavior in mice.[16] After classification, visualization and quantification methods are presented that allow a practitioner to rapidly assess an individual's lifespace and activity patterns.

METHODS

Data Acquisition Device

Nokia N79 SmartPhones (White Plains, NY) with a three-dimensional accelerometer, an assisted global positioning system (GPS), and a wireless transmitter and receiver (class II Bluetooth, Ericsson, Stockholm, Sweden) were used for data collection. Symbian S60 V3FP2 OS (San Francisco, CA) running Python for S60 v1.9.7 (https://garage.maemo.org/projects/pys60) was used for data acquisition. Data were collected using multiple carriers. Network provider did not affect GPS data acquisition.

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Activity Measurement

A custom Python module was used to sample values from the onboard three-dimensional accelerometer (each dimension, x, y, and z, at 10 Hz). Accelerometer (sourced from STMicroelectronics, LIS302DL, by Nokia) dynamic range in x, y, and z directions was −2 to +2 g. Data are written to flash memory and then transmitted by cellular telephone to a secure server. Raw data are conditioned into activity counts using current best practices.[17] Activity counts are determined by integrating data over 1-minute bins. The effect of phone placement on activity counts (data not shown) was evaluated by obtaining simultaneous data streams from telephones placed on the hip (pants pocket), wrist, ankle, and neck (as a pendant). Cellular telephone actimetry data were also compared with data obtained from standard wristwatch style actimeters (ActiWatch-L, Philips Respironics, Bendm OR; MicroMini, Ambulatory Monitoring Systems, Inc., Ardsley, NY).

In-Home Locating

Bluetooth transmitters can be programmed to remain in discovery mode and constantly broadcast a unique identification number: the Bluetooth ID (BTID). Depending upon the device output strength, the receptive field for this transmitter can be limited to approximately six feet and as large as approximately 200 feet. In one home, Bluetooth beacons (BrainBox BL819, Liverpool, UK) and one Plogg (Energy Optimizers Ltd, Grimsby, UK) were placed to cover the ground-floor living space. Two beacons were positioned each in the master bedroom and kitchen and one each in the master bath (next to sink), dressing room, living room, television room, and laundry room. A Plogg (which broadcasts a stronger signal than the BrainBoxes) acting as an “at home” beacon was placed in the center of the home. An additional beacon was placed in the participant’s office at work. For 30 days, the participant carried an N79 SmartPhones (usually in slacks pocket) at all times except when washing. BTIDs were queried every 60 seconds. In the event that two Bluetooth devices were identified in the same query, the analysis was focused on the device with the strongest signal.

In-Community Locating

When line of sight to the satellite was available, the telephones logged GPS coordinate data (longitude and latitude, in degrees) every minute. To eliminate potentially spurious values collected when the device was indoors, GPS coordinates whose time stamp coincided with detection of the at-home or in-office Bluetooth beacon were removed. Detection of this beacon meant that the participant was within a 200-foot radius of the home or office center and probably not outdoors. GPS data were then examined using a histogram to remove any obvious outlying coordinates. Outlines of geographic lifespace were created by mapping the coordinate data using the publicly available GPS Visualizer tool (http://www.gpsvisualizer.com). Lifespace trajectories over 1-, 7-, and 30-day time intervals were created. These trajectories were cross-validated to corresponding composite lifespace scores.[9] To create probability density estimates of in-community lifespace, Universal Transverse Mercator projections of the coordinates were determined according to standard practice.[18] Probability density functions were estimated using a kernel density estimator. GPS coordinates for epochs during which the participant was indoors were inferred from the last known GPS coordinates measured before at-home or in-office beacons were detected.

Participants

Data provided from this proof-of-principal study came from three authors (SJB, CAH, RHC), aged 48, 33, and 27, respectively. SJB and CAH yielded 30 days of data each, and RHC yielded 21 days. Only 1 day of data was lost because of technical failure; the remainder of data loss (11 cumulative days over 81 days of observation) was because batteries ran out at night or the participant was away from the backup telephone. Because carrying a personal cellular telephone has become a feature of many individual's lives, the three participants tightly adhered to the protocol. No participant had any functional limitations during testing. A minimal protocol was employed when collecting long-term activity and lifespace patterns. Procedures for successful cellular telephone data acquisition were reviewed. Participants received two cellular telephones each and sufficient Bluetooth beacons to cover their living arrangements. Participants were asked not to modify their lives or day-to-day activities in any way for this experiment. For experiments focused on validating cellular telephone actimetry counts, ethograph information was obtained through an activity log that the participant kept. To optimize data resolution, participants were asked to break activities into logical episodes for logging while not providing moment-to-moment levels of detail for each activity.

Privacy and Security Considerations

Institutional review board approval for this study was obtained from the human subjects committee at the University of Nebraska Medical Center. All study participants provided informed consent. The data presented here show paths clearly depicting an individual's movement within the community; permission for release of this location data has been explicitly obtained. This information is provided to demonstrate that this technology can measure movement within the community in a way that has high face validity; for future studies, movement trajectories will be de-identified to prevent establishing links between movement paths and specific geographical regions. The initial approach for presenting this data in a de-identified form (kernel density estimation of lifespace, as above) completely removes personally identifying information from the data while allowing lifespace to be appropriately inferred. Without a priori knowledge of participant identity, there is no way to link time-series accelerometry data to specific individuals.

RESULTS

Cellular Telephone Accelerometer Measures Daily Variation in Activity Levels

More than 70 person-days of activity data were collected with the cellular telephones. Figure 1 shows a sample comparison of this approach with a wristwatch actimeter. The cellular telephone was placed in the inner left pocket of a fleece vest; the actimeter was worn on the left wrist. The cellular telephone accelerometer is more sensitive to variations in overall activity. For example, in the cellular telephone data (Figure 1C), episodes of walking or meal preparation are qualitatively more distinct from sedentary behaviors such as watching television and playing cribbage (compared with wristwatch actimeter data in Figure 1D). High levels of sensor activity for ActiWatch and cellular telephone observed while driving may be a function of many factors, including road and shock absorber condition and personal driving style, but in both cases, the GPS can identify driving bouts.

By collecting data using a cellular telephone, a device that many people routinely carry in their day-to-day lives, activity and lifespace measurements can be easily integrated into people's routines over prolonged time periods. The difficulty of obtaining long-duration datasets of individual activity for appropriately sized clinical groups remains a significant limitation of many studies trying to measure activity and energy balance (e.g., Bravata et al19). Figure 1E shows a double-plot actogram (two activity cycles per each line in the plot, with the second cycle of each line the same as the first cycle of the following line) of cellular telephone accelerometer data collected during a 21-day-long field test, demonstrating the relative ease of this approach for noninvasive, long-term activity assessments.

GPS Locations Provide Automated Estimates of Individual Lifespace

Measurement of how individuals move through their community is usually collected using surveys, a method subject to many well-characterized biases (e.g., Bland and colleagues[20–22]). Here, the first example of lifespace data automatically collected using cellular telephone GPS is provided (Figure 2). Note the occurrence of a predominant path from home to work (Figure 2A and D) that is repeated on weekdays. Activities outside of this path reflect the complexities and spontaneous decisions that may characterize higher degrees of functional independence. Not surprisingly, the test participant's lifespace becomes more extensive over longer observation durations (Figure 2D–G). The probability of locating the test participant during this month-long observation is highly skewed to the participant's home and place of work (Figure 2G), with other regions having smaller, but still significant, visit probabilities.

Participant movement trajectories within the community are straightforward to appreciate and have high face validity. Furthermore, these trajectories can be used to calculate an individual's lifespace automatically. In addition to fully anonymizing these data (because it would be possible, albeit technically difficult, to match paths to worldwide road databases), this approach takes advantage of the extensive validation that lifespace metrics have undergone. The same scoring schema as described previously,[10] in which lifespace is a continuous variable valued between 0 and 120 (higher values suggesting greater functional capacity), was used. The maximum daily distance that the participant moves from home is measured. For this participant's residence, trips longer than 5.5 miles constitute activity outside the neighborhood. Using a 1-week averaging window, a continuous lifespace score is automatically calculated for 3 of the 4 weeks of participant observation (Figure 2H). As previously described, this trajectory remains stable for the test participant during the period of observation. Prior studies have shown that lifespace values change over longer observation periods[23] and that even 6-point differences in lifespace can have clinically significant correlates.[24]

Bluetooth Beacons Measure the Temporal Organization and Time Budgets of Day-to-Day Location

For individuals with marked functional limitations, activities are scaled to the dimensions of their home, and the organization of movement within the home may be a health-associated outcome similar to lifespace. Bluetooth beacons were used to quantify the spatial organization of movement within the home (which cannot be assessed using GPS). Results from 48 hours of observation are shown in Figure 3. Using this automated approach, daily patterns of movement (Figure 3A) and an overall location time budget (Figure 3B) could be identified. Time budgets are excellent tools for assessing how a participant allocates time across different activities or regions. For example, this approach visualizes an oft-repeated home routine during which the participant stays with his spouse in the bedroom until she is asleep, rises to perform assorted household chores, and then returns to bed at approximately midnight. Integration of GPS and the at-office beacon permitted determination of when the participant was in transit to work or at the office (green color code in Figure 3). The participant returned home at approximatley 11:00 p.m. on Tuesday, November 3. Review of the participant calendar for that day showed attendance at a university function that did not end until 10:30 p.m. These data demonstrate that at-home and at-work locations can be successfully captured in an automated and accurate fashion.

DISCUSSION

This study provides proof-of-principle data demonstrating that off-the-shelf electronic components, including cellular telephones and Bluetooth transmitters, can measure the temporal and spatial patterns of an individual's activity in a noninvasive, simple, and accurate manner. It further demonstrates that these observations can be made over a substantial period of time. It shows that cellular telephone accelerometers can substitute for substantially more expensive dedicated actimeters while providing equivalent information regarding day-to-day movement and activity and that automated logging of an individual's position when in the community allows a highly nuanced picture of an individual's lifespace to be produced across multiple time scales. It demonstrates that, with minimal loss of personal privacy, highly accurate, room-level resolution can be obtained of participant locations within the home and workplace.

Current system limitations temper the above findings. This article describes activity and lifespace patterns for three participants involved with the research team. These participants thus have more motivation, education, and technological savvy than community-dwelling older adults. The software version initially deployed for this study required the participant to activate multiple applications after starting the telephone, increasing the probability of a data loss event. The current software version activates all data collection and transmission streams automatically when the telephone is turned on and thus is highly usable even for persons with minimal technological skills (because there is no user input needed other than turning on the telephone). In addition, all of the test lifespaces were collected between November and March; climactic conditions may significantly influence lifespace features across large regions of North America.

In addition, for this approach to be adopted on a wider basis, future studies must focus on participant adherence and particularly their ability to successfully carry the study cellular telephone with them as much as possible. Even under ideal circumstances, the participant cannot take the cellular telephone with them for certain activities (e.g., washing, swimming) and probably will not wear the cellular telephone to bed. Ongoing validation trials are focused on determining how these missing events affect overall data quality. The factors that maximize participant adherence for carrying the cellular telephone throughout the day need to be identified. If the validation trials suggest that forgetting the cellular telephone is a considerable problem, future efforts would be focused on moving some system functionalities (particularly activity and Bluetooth measurements) to an easily wearable device such as a wristwatch or pendant.

Additionally, the in-home Bluetooth positioning approach does not provide trajectories of individual movements. Animal studies examining locomotor path data (for which there is an extensive literature) show that the most significant insights come from analyses in which activity is aggregated across specific regions of study (e.g. center vs periphery of an arena when evaluating anxiety, novel region vs trained region when evaluating exploratory behavior25). These experiences suggest that room-level resolution will provide much insight into the organization of human behaviors. Finally, the system is insensitive to brief forays from a given position (because it samples Bluetooth transmitters every minute). For example, an episode in which someone sitting in the kitchen rises, walks to the bedroom for a personal item, and returns to the kitchen within the minute could be missed. Simply increasing the sampling rate does not solve this problem, because more Bluetooth queries markedly decrease device battery life. Future studies will focus on reconfiguration of the Bluetooth beacons so that they concurrently query for the presence of a study cellular telephone. Because the beacons obtain power from high-capacity batteries or alternating current outlets, they will be able to support significantly higher sampling rates than the telephone and provide a redundant data stream to assist quality control of this behavioral data class.

Although this system is nearly ready for clinical deployment, a few remaining factors must be addressed so that trials employing this approach will provide the highest quality data. For example, further efforts are required to fully validate the cellular telephone actimeter across a broad range of activities and individual body habitus (reviewed in17). Different individuals will choose to carry their telephones differently (e.g., pocket, pocketbook, belt loop). It will thus be important to quantify how wearability influences activity counts during self-reported bouts of specific behaviors. Efforts to maximize battery life are also ongoing, to minimize episodes of unanticipated data loss. Until there are battery-life solutions capable of powering the phone for longer than 1 month without charge, participants will continue to be provided with two telephones during these studies, so that one phone can always be charging while the other is actively collecting data.

The most significant finding is the demonstration of a fully automated approach to measuring the time patterns and time budgets of in-home movements. In-home location is difficult to quantify. It is burdensome to document using a journal and is subject to participant to recall and related biases.[26,27] The use of in-home Bluetooth telecommunications provides an opportunity to expand the approach to assess functional behaviors. For example, Bluetooth temperature and lighting sensors can provide simultaneous measures of important indoor environmental conditions that the participant may be experiencing. Bluetooth-based sensors measuring the presence of standing water and electricity consumption may provide insight into personal hygiene and meal preparation. Because there is a remarkable spatial and temporal regularity to most individuals' performance of day-to-day activities,[28] this system may be sensitive to real functional improvements, such as less time in the home dressing area—which may be a surrogate for faster dressing times.

The preliminary data suggest that 1-minute sampling rates provide excellent resolution to determine in-community location. Here, the first automatic determination of an individual's lifespace over different time scales is demonstrated. Lifespace[8] is defined as the extent, frequency, and independence of one's movement trajectories away from a home base. These movements can range from leaving the bedroom to leaving the community. With the modest resolution possible from survey-based lifespace instruments, this concept provides useful measurements of an individual's enacted functional status. The opportunity to have a highly precise, automatically created representation of lifespace will be of significant importance for future studies focused on caring for individuals with functional limitations.

More generally, this approach measures time-dependant geographic data and can thus employ many of the mathematical and statistical techniques developed for geographic information systems (GIS) applications. For example, the concept of time-space graphs and time-space prisms extends the lifespace concept to account for time variation in location more precisely and is particularly useful for finding factors that limit one's movements within the community.[29] A number of econometric models have also been developed to analyze how movement through the community best maximizes an individual's desired goals.30 Both of these approaches may be promising avenues for the development of additional metrics that evaluate how aging affects an individual's enacted functional status. Finally, the current study suggests that healthy human participants move through their home range in a manner quite similar to what has been observed in many other mammalian species, including mouse models readily available for translational studies.16

In conclusion, it is feasible to obtain highly precise measures of an individual's activity and lifespace using a combination of inexpensive Bluetooth transmitters, commercially available cellular telephones, and the global telecommunications network. Adoption of automated measures of activity and lifespace have the potential to provide a more-accurate phenotype of an individual's enacted function before or after enrollment in a clinical trial. This approach will also be the initial stepping point for developing more advanced metrics that will ultimately classify individual activity and simultaneous location data into defined functional behaviors and use these classifications to effectively and inexpensively identify frail community dwelling adults at risk for new-onset functional loss.

Acknowledgments

We thank Dr. William L. Lyons for critical reading and suggestions regarding this manuscript. The authors thank Michael Hempel, PhD, and Hamid Sharif, PhD (University of Nebraska, Omaha, NE) for help selecting Brainbox Bluetooth transmitters. We thank Ms. Sharon Welna for assistance in addressing University of Nebraska Medical Center security concerns related to data transmission and Mr. Joseph Ziskovsky for assistance setting up the data receipt server.

This work was funded by a grant to SJB from the Vada Kinman Oldfield Foundation and startup support provided from the University of Nebraska Medical Center. EHG was supported by National Institute of Mental Health, National Institutes of Health Grant K08 MH071671.

Sponsor's Role: The sponsors did not have any role in the design, methods, participant recruitment, data collection, analysis, or preparation of the manuscript.

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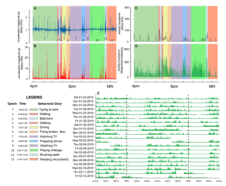

Figure 1.
Cellular telephone accelerometer has high face validity for measuring individual activity. (A) Magnitude of unprocessed signal from accelerometer as a function of time, matched to participant activities manually logged on diary; color and numerically coded per legend. Ethogram generated using participant log. (B) Accelerometer signal after passage through a 50-component finite impulse response filter. (C) Accelerometer signal from B integrated over consecutive 1-minute bins to determine activity counts. (D) Simultaneous activity counts measured using an ActiWatch-L. The cellular telephone–derived actimetry signal of C during epochs of low physical activity (7:50–9:00, 9:25–9:55, 9:55–11:25) has a higher face validity than the wristwatch actimeter signal of D. (E) Double-plot actogram of participant activity over 21-day observation period. Activity counts (depicted in green) calculated as described in the Methods section. Missing data depicted as breaks in the activity trace and account for approximately 8.4% (42.5 hours of the total 504 hours) observation. Dotted lines are at midnight Central Standard Time.

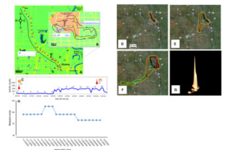

Figure 2.

Simultaneous measurement of in-community location, physical activity, and geographic lifespace using cellular telephones. (A) Map depicting participant commute to work. Waypoints (in red) sampled every 60 seconds during trip. Coordinates mapped using www.gpsvisualizer.com. Numbers next to selected waypoints correspond to numbers in the time versus activity count graph at bottom. A selected expansion of the time immediately before waypoint 3 is provided in inset (A) and suggests that, for this participant, little accelerometer activity was detected during driving. (B) Upon arrival at the University of Nebraska Medical Center campus, the participant then walked around the campus. Again, waypoints (in blue) were sampled every 60 seconds during this trip. Inset (B), between waypoint 7 and 8, depicts the participant stopped at the corner of 42nd Street and Emile, waiting for the traffic light to change before crossing the street. Inset (C) was randomly chosen during a period of continuous ambulation and suggests the possibility of obtaining gait speed from this quasiperiodic unconditioned accelerometer trace. Tick marks on *x* and *y* axes for all insets are of the same magnitude and depict 0 to 3 g force for the *y* axis and 60 seconds of time for the *x* axis (across entire range). (C) Activity counts for the entire trip are shown in the time versus activity count graph and are cross-referenced to current weather conditions (obtained from http://www.wunderground.com, first from the Blair, NE, station, second from the nearest Omaha, NE, station). Second panel depicts in-community location over day (D), week (E), and month (F) interval measured using cellular telephones. Yellow outline shows the extent of geographic movement for each interval. The path in D is the participant commute from home to work (highlighted in A). The more-elaborate trip of E (depicted in yellow circles) occurred when the participant attended a conference in Ashland, Nebraska. The monthly lifespace also depicts a pleasure trip to central Nebraska to visit a colleague's farm (green circles) and a trip with the spouse to Council Bluffs, Iowa (red circles). (G) Probability density graph for 1 month in community location. The two largest peaks correspond to the participant's home and place of work. The probability density representation is one way of quantifying the geographic aspect of lifespace while providing complete anonymity for the participant. (H) Continuous measurement of lifespace scores as determined from in-community locations. Scores calculated using Lifespace Questionnaire. Because lifespace scores determined using this method assess mobility over the past week, only 3 weeks of scores were determined from 1 month of data. The decrease in lifespace score noted from November 24, 2009, reflects the onset of the Thanksgiving holiday, during which the participant did not commute outside of the immediate home neighborhood.

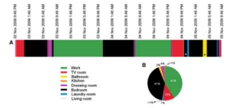

Figure 3.

Simultaneous activity and Bluetooth location sensing to study organization of indoor activities. (A) Timeline reveals 2 representative days of data collected using Bluetooth beacons and cellular telephone. Legend as above. This automated approach captured 1 day on which the participant came home late after a work-related meeting. *An at-home routine during which the participant reads in bed with his spouse and then returns to work is also captured. (B) Pie chart shows time budget for this period of observation. Time budget value determined from in-home positioning data provided by Bluetooth beacons and cellular telephone.