IEEE Journal of Translational Engineering in Health and Medicine

Received 21 March 2016; revised 6 June 2016 and 4 September 2016; accepted 22 September 2016.
Date of publication 8 December 2016; date of current version 9 December 2016.

Digital Object Identifier 10.1109/JTEHM.2016.2620971

Low-Cost Sensor System Design for In-Home Physical Activity Tracking

SIDDHARTHA NAMBIAR[1], ALEXANDER NIKOLAEV[2], MELISSA GREENE[3], LORA CAVUOTO[2], AND ANN BISANTZ[2]

[1]Department of Industrial Engineering, North Carolina State University, Raleigh, NC 27606, USA
[2]University at Buffalo, The State University of New York, Buffalo, NY 14226, USA
[3]Department of Design Science Engineering, University of Michigan, Ann Arbor, MI 48102, USA

CORRESPONDING AUTHOR: S. NAMBIAR (snambia@ncsu.edu)

ABSTRACT An aging and more sedentary population requires interventions aimed at monitoring physical activity, particularly within the home. This research uses simulation, optimization, and regression analyses to assess the feasibility of using a small number of sensors to track movement and infer physical activity levels of older adults. Based on activity data from the American Time Use Survey and assisted living apartment layouts, we determined that using three to four doorway sensors can be used to effectively capture a sufficient amount of movements in order to estimate activity. The research also identified preferred approaches for assigning sensor locations, evaluated the error magnitude inherent in the approach, and developed a methodology to identify which apartment layouts would be best suited for these technologies.

INDEX TERMS Biomedical monitoring, senior citizens, sensors, smart homes, geriatrics, gerontology, successful aging.

I. INTRODUCTION

Sedentary living is increasingly common and contributes to approximately two million deaths per year – one of the top ten causes of preventable deaths worldwide [12]. Increased levels of physical inactivity have resulted from changes to the modern physical, economic, and social environment. Moreover, the integration of advanced technologies has greatly reduced the amount of physical activity required for living and interacting socially [10].

Commercial solutions for physical activity tracking are increasingly available [9], leading to a strong academic interest in physical activity monitoring, particularly within the context of aging-in-place. However, the technology intended to promote independent living among older adults may present usability and acceptance concerns. Older adults experience declines in physical, sensory, and cognitive capabilities as they age, which creates unique human-computer interaction design challenges that require careful consideration [1]. Older adults may experience apprehension from a lack of familiarity with advanced technology and obtrusiveness and privacy concerns. Thus, research should be dedicated to developing physical activity tracking systems specific to the needs of aging adults.

This work applies simulation and optimization techniques to demonstrate the possibility of collecting sufficient data to predict movement amounts of elderly adults, within their homes, using a small number of optimally placed sensors. Our research found that it is possible to characterize the amount of error in these predictions, and attain globally optimal solutions for sensor placement in various senior living apartment layouts. This approach can therefore be valuable in obtaining low cost movement data which can support physical activity monitoring and promotion.

II. REVIEW OF LITERATURE

Current trends in physical activity monitoring take two forms: active (typically, wearable) sensor systems which require user actions to position and/or activate, and passive sensor systems (typically, external systems with no sensors worn by the user) which collect information without active initiation by the user. *Active sensing technologies* typically collect physiological data from body-worn or clothing-embedded sensors. Current devices – e.g., unobtrusive wristbands or shirts – are typically low-cost, small, and powerful [6]. Such sensors are used to detect and record attributes including motion, location, temperature, steps taken/floors climbed, and activity duration/intensity [2].

However, active sensors present challenges in terms of data collection and quality, particularly for older adults. First, research suggests that these technologies are not often developed with elderly consumers in mind [1], [4], [9]. Active sensing systems must be consciously affixed to the body,

turned on, and checked to ensure they are functioning properly. Often they require users have the technological sophistication connect and download data from the device. Some depend on accelerometers for activity recognition and are therefore subject to error depending on placement on the body [8], [13], [14]. Additionally, some research has suggested that technologies worn on the wrist may be inappropriate for recognizing slow-speed ambulation activities. Accidental arm movements can generate incorrect measurements and activity predictions, which may render these tools ineffective at adequately reflecting a user's energy expenditure. Because older adults are often limited in the types of activity they can participate in, basic ambulation actions are sometimes their *only* observable activities. Walking speed declines with advanced age; therefore, technologies that are not precise enough to accurately reflect these movements are inadequate for use in this particular demographic.

As an alternative to active sensors, *passive* systems have been proposed, where sensors are attached to objects in the user's environment, and inferences regarding the user's physical activity are made based on data captured by the sensors [7]. Unlike the active systems described above, users are not required to don, control, or download data from the sensors. TigerPlace is an example of a residential community which extensively implemented sensors to support safe aging-in-place. A dense network of sensors allows researchers to integrate information from motion, bed, and stove sensors with a video sensor network and a behavioral reasoning system [12]. However, as the number of sensors included in a system rises, the quantity and the complexity of the data collected increases, as does the cost to transmit the data [11], making it impractical for widespread implementation.

In contrast, some other recent work has focused on more sparse passive monitoring systems. One such system [5] involves the use of ultrasonic range finders mounted in doorways to sense people as they walk between rooms. The system can differentiate among individuals based on height, infers their walking direction using signal processing, and identifies their room location based on the sequence of doorways through which they pass. While promising in terms of feasibility, using such low-density sensors raises questions regarding the degree to which the collected data can reliably measure an individual's physical activity level.

Our research considers whether or not a sparse network of doorway sensors could be useful for reliably capturing physical activity levels in a home. We conducted a simulation study is to determine the minimum number of doorway sensors required to produce useful information regarding the movement patterns of individuals within the home, as well as the optimal sensor placement. The following research questions are addressed:

1) Whether a doorway-based system utilizing a small number of low-cost sensors is useful in predicting the amount of in-home movement.
2) Whether the amount of error in these predictions could be characterized as sensor number and placement changes to accommodate differences in senior living apartment layouts.

These questions are explored using optimization and regression analyses involving five different apartment layouts taken from existing senior living communities,[1][2][3][4] and simulated physical activities based on the American Time Use Survey (ATUS).

III. DATA SET CREATION

A. ACTIVITY DATA

Data were obtained from the ATUS micro-data files, made available by the US Bureau of Labor Statistics.[5] These surveys capture leisure and work-related activities of over 148,000 Americans from 2003 to 2013, providing activity-level information including activity code, location, duration, and activity start and stop times, on a per individual basis for one particular day. Table 1 provides a snapshot of a data subset contained in the ATUS activity file. For each activity case ID, a combination of the three tier codes (TUTIER) indicates the activity performed. For instance, a combination of 01 (TIER1), 02 (TIER2) and 01 (TIER3) corresponds to the activity of 'washing, dressing and grooming oneself'. A detailed list of what the activity codes correspond to are provided in the Activity Coding Lexicons.[6] The snapshot in Table 1 indicates five different activities performed by a particular individual and provides information regarding the ID of the individual (TUCASEID), serial number of the activity performed (ACT), the duration of the activity performed (DUR) and what the actual activity was (combination of TIER1, TIER2 and TIER3).

TABLE 1. A sample subset of data found in ATUS activity file.

TUCASEID	ACT	DUR	TIER1	TIER2	TIER3
20060101020210	*1*	*210*	*01*	*01*	*01*
20060101020210	*2*	*40*	*13*	*01*	*31*
20060101020210	*3*	*40*	*01*	*05*	*01*
20060101020210	*4*	*10*	*11*	*01*	*01*
20060101020210	*5*	*30*	*18*	*05*	*01*

B. LOCATION DATA

A standard set of locations was identified by analyzing five senior citizen apartment layouts from communities across

[1] http://www.infrahousing.com/verandah-project.html (1-3)
[2] http://www.sukhshanthi.com/index.php/specification/floorplans
[3] http://www.codechicdesigns.com/day-care-center-floor-plans/3/sample-daycare-floor-plan/
[4] http://www.swanbuild.com.au/kempton/
[5] http://www.bls.gov/tus/#data
[6] http://www.bls.gov/tus/lexicons.htm

the United States. These locations included: kitchen, dining room, bedroom, washer/dryer, bathroom, and outside (external to the apartment).

The activity codes obtained from the ATUS were then mapped to a presumed activity location by manually creating a mapping from the activity type to the activity location. For example, the code 10101 corresponds to the activity 'sleeping', which we infer as having occurred in the bedroom.

TABLE 2. Time spent in rooms statistics (minutes).

	Bath Room	*Bed Room*	*Kitchen*	*Living Room*	*Washer*	*Outside*
Mean	40.4	1091.7	116.5	121.8	10.9	202.2
Std deviation	38.6	269.7	80.9	141.5	35.1	197.8

The average number of activities (non-unique) undertaken daily by each individual was 17.9 (s.d. = 7.1). Additional statistics regarding the time spent by the individuals in each of the rooms, based on the ATUS data and our activity-room mapping, are provided in Table 2.

C. APARTMENT CONNECTIVITY GRAPH CREATION

To capture the relationship between movements in different rooms, a connectivity graph G_s was defined for each apartment $s \in S$ as an ordered pair $G_s = (V, E)$, comprising a set of vertices $V \in \{\text{set of rooms in apartment } s\}$ and a set of edges $E \in \{(i, j)\, \forall i, j \in V\}$ if room i and room j are connected by a doorway in apartment G_s. Fig. 1 shows the connectivity graph between rooms according to the floor plan for a particular apartment. Each node corresponds to a room, and weights are assigned to the edges based on the sequence of rooms visited, representing the number of times a person travelled between the two nodes (rooms) at the end points of a particular edge.

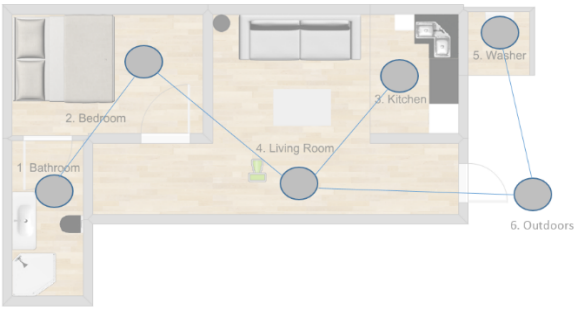

FIGURE 1. Sample Connectivity graph for a particular floor plan. Note: The washer is placed outside the apartment as a laundromat.

Table 3 shows example edge weights in a tabular format. The complete dataset contains 2393 entries, one for each individual whose activity is being analyzed.

TABLE 3. Sample edge weight values for three individuals. The rooms are coded in numbers corresponding to Fig. 1 (1: Bathroom, 2: Bedroom, 3: Kitchen, 4: Living Room, 5: Laundry, 6: Outdoors).

	5-4	3-4	3-2	3-1	3-6
Individual 1	2	7	4	0	1
Individual 2	4	5	7	0	9
Individual 3	2	5	6	2	5

IV. COMPUTATIONAL ANALYSES

A. OPTIMIZATION STUDY OF OPTIMAL SENSOR PLACEMENTS FOR MAXIMUM ACTIVITY DETECTION

An integer programming model was constructed to study the percent of activity that could be detected by a limited number of placed sensors. Let n_i^j denote the number of crossings by person j in pathway i, such that each pathway i is an edge connecting two nodes (rooms) in the connectivity graph for that floor plan. Let d_i denote the length of pathway i. The following program returns the values of binary decision variables x_i that indicate, for each pathway i, whether one sensor out of the n sensors available should be placed there, to achieve the maximum expected amount of activity detected over the population of all individuals with different movement patterns.

$$Max : \sum_j \sum_i (n_i^j d_i) \times x_j. \tag{1}$$

Subject to:

$$\sum_j n_i^j d_i x_j \leq \left\{ \sum_j n_i^j d_i \right\} w, \quad i \in \{1 \ldots 2393\}, \tag{1a}$$

$$\sum_j x_j \leq n, \quad x_j \in \{0, 1\}. \tag{1b}$$

The objective function coefficients in (1) capture the total distance travelled by every individual through each edge of the connectivity graph. The constraint (1a) ensures that the sensor placement is subject to the detection of at least $w \times 100\%$ of every person's activity. Constraint (1b) limits the number of sensors that can be allocated and ensures x_i is binary.

Varied instances of the optimization problem were executed in MATLAB R2013a. Table 4 presents the optimization study results as the fraction of total activity detected by the number of sensors and floor plan.

Approximately 59% of all activity was detected with the use of just two sensors, increasing to approximately 85% with the addition of a third sensor. Thus, we can conclude that it is feasible to place a limited number of sensors and be able to detect a large percentage of activity.

It is worth noting that results obtained from the optimization technique are identical to those obtained from solving the problem via a greedy approach. This is made possible in the current instance of the problem due to lack of more complex

TABLE 4. Fraction of total activity detected with variation in floor plan and number of sensors placed based on optimization model.

	n = 2	n = 3	n = 4
Floor Plan 1	0.5892	0.8548	0.9785
Floor Plan 2	0.5892	0.8548	0.9785
Floor Plan 3	0.5967	0.8533	0.9783
Floor Plan 4	0.6264	0.8687	0.9806
Floor Plan 5	0.5817	0.8522	0.9781

constraints which could arise depending on requirements with regards to where the sensors can or cannot be placed.

B. REGRESSION ANALYSIS OF INDIVIDUAL MOVEMENT PATTERNS

The optimization study established that doorways can be selected for placement of sensors so as to detect the maximum possible amount of each individuals' movement activity. In the regression analysis, our goal was to infer how well one could predict distance travelled by an individual based on the number of passes between various doorways ('doorway crossing data'), with sensors used at some (but not all) doorways.

Due to a lack of data regarding the exact distance travelled by the individuals (which corresponds to the dependent variable in the regression analysis), distance travelled can be calculated as a linear function of the number of passes between each doorway,

$$D_i = \sum_{(k,j)\in E} n^i_{jk} \times d_{kj}, \tag{2}$$

where i is the index of the individual under consideration, D_i is the total distance travelled by the individual, d_{kj} is the distance between rooms i and j in the floor plan under consideration, E is the set of nodes for the connectivity graph under consideration, n^i_{kj} is the number of passes made between rooms k and j by the individual in the floor plan under consideration.

The first 1500 data points in the ATUS dataset were used for training and the remaining 893 for testing. With the distance calculated in (2) as the dependent variable, and the number of crossings at a combination of the doorways (from the 'doorways crossings data') taken n at a time (where n corresponds to the number of sensors to be placed), a series of regression analyses (using the method of least squares, owing to a linear model) were performed to determine the doorway locations where sensor placement would produce the highest R^2. Table 5 displays the results of the optimal sensor assignment for different floor plans and numbers of sensors, providing the optimal sensor locations and the corresponding R^2.

TABLE 5. Results for regression analysis to determine the optimal placement of sensors in order to obtain a model describing the best predictive analysis (i.e., highest R^2 value).

Floor Plan index	Number of Sensors	Location of Sensors	R^2 value
Floor Plan 1	2	Bat-Bed, Bed-Liv	0.866
	3	Bat-bed, Bed-Liv, Liv-Out	0.956
Floor Plan 2	2	Liv-Out, Bed-Liv	0.812
	3	Bat-Bed, Bed-Liv, Kit-Liv	0.902
Floor Plan 3	2	Liv-Out, Bed-Liv	0.8
	3	Liv-Out, Bed-Liv, Liv-Bat	0.910
Floor Plan 4	2	Bed-Liv, Kit-Out	0.936
	3	Kit-Liv, Bed-Liv, Kit-Out	0.964
Floor Plan 5	2	Kit-Liv, Bed-Liv,	0.851
	3	Bat-Liv, Kit-Liv, Bed-Liv	0.881

Table 5 displays a large R^2 value (approximately 0.92 on average) for the placement of just three sensors, indicating that a predictive analysis is possible with a limited number of sensors.

Despite the overall large R^2 values, it is possible for the model to prove unreliable (i.e., have large residual errors) for specific cases. To assess the robustness of the predictions across the potential population, errors resulting from a predictive analysis of movement patterns, based on the ATUS data, were analyzed. In particular, information obtained from table 3 (which was, in turn, generated from the ATUS data) was used to determine the 'Actual Distance' (AD) travelled by an individual. In contrast, the 'Perceived Distance' (PD) was obtained by running the regression analysis of the distance travelled, based on data from placing a limited number of sensors. The optimal regression equation obtained was used to generate the 'Perceived Distance' (PD) and compared against the 'Actual Distance' (AD) to report the percentage error,

$$Error\% = 100 \times \left(\frac{AD - PD}{AD}\right)\%. \tag{3}$$

Equation (3) returns the value by which the 'Perceived Distance' (PD) differs from the actual distance. Fig. 2 shows the percentage error values over the testing population obtained from the regression analysis on floor plan 1 with three sensors.

Errors were less than 25.8% for 85% of all individuals, indicating that it is feasible to perform a predictive analysis of movement patterns. The errors are skewed towards negative values signaling that the regression analysis tends to *overestimate* the distances travelled by the individuals.

Fig. 3 demonstrates this phenomenon, by plotting percentage error for each of the 1007 individuals modeled, arranged in order of least- to most-distance travelled. As the AD travelled increases, the percentage error in the calculation of the PD travelled decreases. Similar performance patterns are observed with other floor plans.

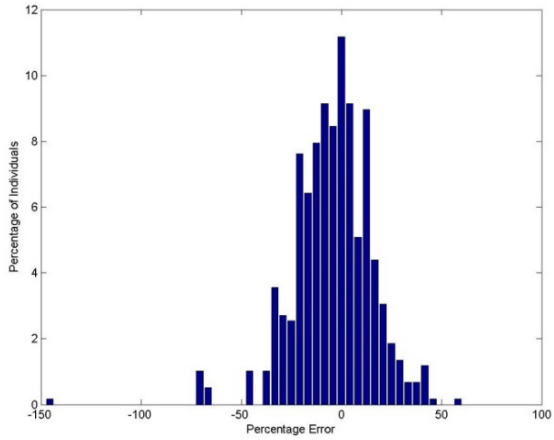

FIGURE 2. Histogram of error percentage in computing the perceived distance travelled (via regression equation) for each of the test data points (each point corresponding to a unique individual).

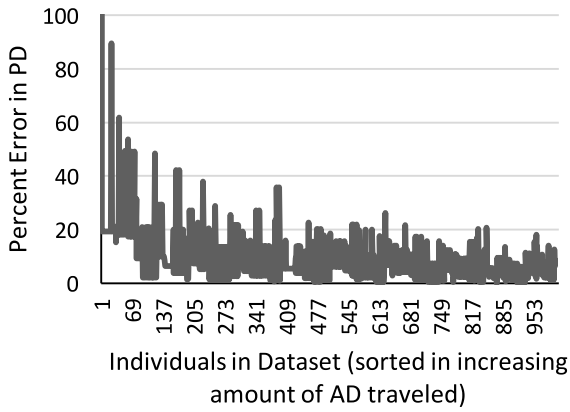

FIGURE 3. Plot describing the decrease in percent error in perceived distance (PD) with an increase in actual distance (AD) travelled by the members of the dataset.

C. SENSITIVITY OF CORRECT ACTIVITY LOCATION IDENTIFICATION

One potential drawback of both the optimization study and the regression analysis is that they may be overly dependent on the way in which we assigned activity codes to location (rooms). We, therefore, studied how the uncertainty/error in this assignment could have affected the above results.

Given a particular optimal sensor placement strategy based on possibly incorrect activity-to-location assignments, one can quantify the extent of the percentage error in PD due to the incorrect assignments. To this end, samples of 'doorway crossings data' for all individuals were drawn by randomly assigning activities to location codes in each sample; the mean percentage error of the PD travelled by the individuals was computed from the regression study (with respect to optimal sensor location assignment), and the variability in these mean percentage error values was assessed, across the samples. The random activity implies that a particular activity, e.g., watching TV, is assigned a location at random from the set of all available rooms in the floor plan. Given the optimal sensor placements for different floor plans (Table 5), Table 6 shows the possible error in placing the sensors in these locations if the activity codes had been assigned incorrectly in the first place.

TABLE 6. Results for mean and variance of mean percentage error values for the randomized sampling experiment.

Floor Plan Index	Number of Sensors	Optimal Location of Sensors	R^2 value	Mean Percentage Error*
Floor Plan 1	2	Bat-Bed, Bed-Liv	0.866	14.16 ± 1 .75
	3	Bat-bed, Bed-Liv, Liv-Out	0.956	10.54 ± 1.58
Floor Plan 2	2	Liv-Out, Bed-Liv	0.812	21.69 ± 2.34
	3	Bat-Bed, Bed-Liv, Kit-Liv	0.902	14.86 ± 2.09
Floor Plan 3	2	Liv-Out, Bed-Liv	0.8	20.94 ± 1.80
	3	Liv-Out, Bed-Liv, Bed-Bat	0.910	11.12 ± 0.74
Floor Plan 4	2	Bed-Liv, Kit-Out	0.936	23.95 ± 3.43
	3	Kit-Liv, Bed-Liv, Kit-Out	0.964	8.84 ± 1.05
Floor Plan 5	2	Kit-Liv, Bed-Liv,	0.851	22.13 ± 2.47
	3	Bat-Liv, Kit-Liv, Bed-Liv	0.881	13.29 ± 1.80

Table 6 indicates that the variance in mean percentage error values is reasonably small. This is encouraging, as even if some activity codes were to be assigned incorrectly, the sensor placements would still hold up for a robust regression analysis.

V. DISCUSSION AND CONCLUSIONS

This study shows that a small network of low-cost, minimally obtrusive sensors which tracks movement between rooms is a promising solution for monitoring the in-home physical activity of older adults. Results indicated that placing three sensors could lead to an average regression coefficient of determination value of 0.922 for the five floor plans considered in this study, indicating the feasibility of a small, low-cost sensor system in a number of different environments. It is also possible to characterize movement patterns and errors for a large number and type of individuals by varying sensor number and placement.

A. LIMITATIONS

It is not unexpected that the R^2 values would turn out as high as they did, especially with two and three sensors, since the originally calculated distance travelled metric is, in itself, an approximation calculated relying on a linear equation [eq. 1], which assumes straight-line travel between the centers of

two rooms. Moreover, data regarding the number of passes between the various doorways is incorporated with a model involving specific floor plans, for analysis purposes. The actual movement patterns of the individuals would have been based on their own respective house plans.

Another potential source of error in this study is the method of data preprocessing: information regarding the rooms in which the activities occurred was not always available and could be subject to considerable variation between individuals. Nonetheless, the data obtained from the simulation study is practically useful and results indicate that these limitations are unlikely to affect overall system performance.

Using the algorithm to outfit actual apartments in sensors would depend on specific floor plans and as such would need to be rerun for different apartment layouts. However, the model is fairly robust and resourceful enough that multiple reruns become a trivial matter. This is evident from the fact that a single instance of the algorithm would not involve more than 10-20 variables and constraints.

B. APPLICATIONS AND FUTURE WORK

Exploring methods of unobtrusive physical activity monitoring could have applications beyond supporting aging-in-place. For example, it could be used to monitor and provide feedback for individuals rehabilitating at home post-surgery, or generally provide feedback about activity levels to individuals concerned about wellness. Future work should validate these models by comparing information that could be gained from optimal sensor placement with that gained from wearable activity trackers, in specific apartment settings. Results from the study also suggest that certain floorplans are more conducive to collecting valuable activity data. It may be possible to design apartment layouts specifically to enable high reliability data collection with a sparse sensor network. An important next step in this line of research involves confirming the results with an actual series of experimental trials to gauge the overall impact of the methodology by incorporating a series of different floor plans.

REFERENCES

[1] J. Goodman and J. Lundell, "HCI and the older population," *Interacting Comput.*, vol. 17, no. 6, pp. 613–620, 2005, doi: 10.1016/j.intcom.2005.09.001.

[2] K. Greene. (2008). *Self Surveillance | MIT Technology Review*, MIT Technology Review, accessed on Jun. 22, 2015. [Online]. Available: http://www.technologyreview.com/news/410806/self-surveillance/

[3] B. K. Hensel, G. Demiris, and K. L. Courtney, "Defining obtrusiveness in home telehealth technologies: A conceptual framework," *J. Amer. Med. Inform. Assoc.*, vol. 13, no. 4, pp. 428–431, 2006, doi: 10.1197/jamia.m2026.

[4] J. Herz. (2015). *Wearables Are Totally Failing the People Who Need Them Most | WIRED*, WIRED, accessed on Jun. 22, 2015. [Online]. Available: http://www.wired.com/2014/11/where-fitness-trackersfail/

[5] T. W. Hnat, E. Griffiths, R. Dawson, and K. Whitehouse, "Doorjamb: Unobtrusive room-level tracking of people in homes using doorway sensors," in *Proc. 10th ACM Conf. Embedded Netw. Sensor Syst. (SenSys)*, 2012, pp. 309–322.

[6] O. D. Lara and M. A. Labrador, "A survey on human activity recognition using wearable sensors," *IEEE Commun. Surveys Tut.*, vol. 15, no. 3, pp. 1192–1209, 3rd Quart., 2013, doi: 10.1109/surv.2012.110112.00192.

[7] L. Chen, J. Hoey, C. D. Nugent, D. J. Cook, and Z. Yu, "Sensor-based activity recognition," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 42, no. 6, pp. 790–808, Nov. 2012, doi: 10.1109/tsmcc.2012.2198883.

[8] U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher, "Activity recognition and monitoring using multiple sensors on different body positions," in *Proc. Int. Workshop Wearable Implant. Body Sensor Netw. (BSN)*, Apr. 2006, pp. 112–116, doi: 10.1109/bsn.2006.6.

[9] P. Mcfedries, "Tracking the quantified self [Technically speaking]," *IEEE Spectr.*, vol. 50, no. 8, p. 24, Aug. 2013, doi: 10.1109/mspec.2013.6565555.

[10] N. Owen, G. N. Healy, C. Matthews, and D. W. Dunstan, "Too much sitting: The population-health science of sedentary behavior," *Exerc. Sport Sci. Rev.*, vol. 38, no. 3, pp. 105–113, 2010, doi: 10.1097/jes.0b013e3181e373a2.

[11] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen, "Activity classification using realistic data from wearable sensors," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 119–128, Jan. 2006, doi: 10.1109/titb.2005.856863.

[12] M. J. Rantz *et al.*, "TigerPlace: An innovative educational and research environment," *Reducing Risks Health, Promoting Healthy Life*, vol. 288, no. 16, pp. 84–91, 1974, doi: 10.1001/jama.288.16.1974.

[13] E. M. Tapia *et al.*, "Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor," in *Proc. 11th IEEE Int. Symp. Wearable Comput.*, Oct. 2007, pp. 37–40, doi: 10.1109/iswc.2007.4373774.

[14] Z.-Y. He and L.-W. Jin, "Activity recognition from acceleration data using AR model representation and SVM," in *Proc. Int. Conf. Mach. Learn. Cybern.*, Jul. 2008, pp. 2245–2250, doi: 10.1109/icmlc.2008.4620779.

SIDDHARTHA NAMBIAR , photograph and biography not available at the time of publication.

ALEXANDER NIKOLAEV , photograph and biography not available at the time of publication.

MELISSA GREENE , photograph and biography not available at the time of publication.

LORA CAVUOTO, photograph and biography not available at the time of publication.

ANN BISANTZ, photograph and biography not available at the time of publication.