Title: Predicting Physical Activity Levels in Individuals with Schizophrenia through Integrated Global Positioning System and Accelerometer Data

Author Names and affiliations

Amir Mohammad Amiri[a], Shivayogi V. Hiremath[a,b], Mark S. Salzer[c,d], Gretchen Snethen[a,d]

[a]Department of Health and Rehabilitation Sciences, College of Public Health, Temple University, 1101 W. Montgomery Ave. 3rd Floor, Philadelphia, PA 19122, USA

[b]Department of Electrical and Computer Engineering, College of Engineering, Temple University, 1947 North 12th Street, Philadelphia, PA, 19122, USA

[c]Department of Social and Behavioral Sciences, College of Public Health, Temple University, 1301 Cecil B. Moore Avenue, Philadelphia, PA, 19122, USA

[d]Temple University Collaborative on Community Inclusion of Individuals with Psychiatric Disabilities, Temple University, 1700 N. Broad Street, Philadelphia, PA, 19122, USA

E-mail Address

Amir Mohammad Amiri: Amir.Amiri@temple.edu

Shivayogi V. Hiremath: Shiv.Hiremath@temple.edu

Mark S. Salzer: Mark.Salzer@temple.edu

Gretchen Snethen: Gsnethen@temple.edu

Corresponding Author

Shivayogi V. Hiremath, Ph.D.

Phone: 215-204-0496; Fax: 215-204-9050

Email: Shiv.Hiremath@temple.edu

Postal Address: Personal Health Informatics and Rehabilitation Engineering Laboratory, Pearson Hall 40, 1800 N. Broad Street, Philadelphia, PA 19121.

Keywords

Physical Activity; Global Positioning System; Accelerometer; Schizophrenia; Location

Abbreviations

Physical Activity (PA)

Personalized Physical Activity Level estimation for specific Locations over time (PerPAL)

Global Positioning System (GPS)

Vector Magnitude (VM)

Density-Based Spatial Clustering of Applications with Noise (DBSCAN)

To the Editors

Research has documented that individuals with schizophrenia spend a significant amount of time in sedentary activity and often do not meet physical activity (PA) guidelines (Stubbs et al., 2016). Environmental factors have long been studied as facilitators or barriers to PA. Among individuals with schizophrenia, environmental factors are known to predict walking and moderate to vigorous PA (Vancampfort et al., 2013). Additionally, environmental characteristics explain 16.8% of sitting time of individuals with schizophrenia (Vancampfort et al., 2014), with factors such as neighborhood infrastructure (e.g., sidewalks or parks) or access to fitness equipment in the home reducing time spent in sedentary behavior. Consistent with Barker's Behavior Settings Theory (Schoggen, 1989) this study is predicated on the expectation that certain locations are associated with behaviors that involve more or less PA. Thus, there is a need to study current PA levels associated with certain locations in the community, which could lead to development of ecological interventions that are personalized to a person's time and location preference to maximize PA performance. To address this need, we propose a new methodology called Personalized PA level estimation for specific Locations over time (PerPAL) to better predict PA levels by location. The development of the personalized models involves identifying recurring locations (Townley et al., 2018) for an individual and using their baseline PA data, location, and time-window to predict future PA levels for specific locations (Brusilovskiy et al., 2016) and time-windows.

Methods

The study was approved by the city and the university-based Institutional Review Boards. Participants were diagnosed with a schizophrenia-spectrum disorder, between the ages of 18-64, and had a desire to increase participation in the community.

Participants wore a tri-axial accelerometer (ActiGraph GT3X) on their non-dominant wrist and carried a study-based cellphone that ran AccuTracking software to collect the GPS sensor data every minute. GPS data (longitude and latitude) were used to identify recurring and unique locations visited by the participant during the course of the study. The acceleration information from the accelerometer was used to assess the PA levels of the participant. The acceleration data was collected in 10-second epochs for a week as the participants went about performing their regular activities in the community at baseline and follow-up (six months later). Vector Magnitude (VM) was used to quantify the intensity of PA levels for each participant.

Research has used GPS data to compute travel distance from the user's identified geo-locations and mobility patterns (Adams et al., 2015; Carlson et al., 2015). The novelty of the PerPAL model development process is based on a two-step process of: i) identifying recurring locations, and ii) developing personalized models that use an individual's baseline PA data, location, and time-window to predict their future PA levels at specific locations and time-windows. First, recurring and unique locations were identified by using Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Birant and Kut, 2007) for each individual over a weekday. The parameters chosen for the DBSCAN algorithm to identify locations of interest (centroid of clusters) included distance between two GPS coordinates to be less than or equal to 200 meters and a minimum of 10 points (visits) per cluster. A location was classified as recurrent if the participant visited it more than 10 times during a week and s/he spent more than 10 minutes in the location. Second, personalized models that use an individual's baseline PA data, location, and time-window were developed to predict future PA levels at specific locations and time-windows. Baseline and follow-up PA level, in terms of magnitude of PA performed, during four six-hour time-windows at each location were calculated. Linear regression analysis was used as part of the second step of PerPAL model development process for each individual. The regression model used PA levels for various locations and time-windows during baseline testing to estimate PA levels at follow-up testing.

Results

Ten participants with schizophrenia-spectrum disorder took part in this study. Eight were female and the average age of the participants was 54.8 (SD = 5.3, range 45-62) years. PA patterns over time and locations indicate that a combination of accelerometer and GPS data will assist us with predicting PA levels for future sessions when specific location and time-window are known (Supplementary Figure 1).

Table 1 shows the number of locations identified by the DBSCAN algorithm and the PA levels for each participant during the four time-windows. The PA levels and the number of locations across all time-windows have a similar pattern for the baseline and follow-up sessions. Based on this information we identified locations that were common to both the baseline and follow-up testing sessions for developing personalized models.

PerPAL predictor models were developed using linear regression analysis. The PerPAL models were significant for seven of the ten participants ($p<0.05$) with the models explaining 89% to 99% of the PA level variation (Supplementary Table 1). For the remaining three participants the models explained 94% to 99% of the PA level variation. The mean (SD) error of the PerPAL models ranged from an underestimation of 6.38% (30.0%) to an overestimation of 2.95% (17.5%).

Discussion

Results from our study indicate that PA levels for individuals with schizophrenia are distributed over location and time for each individual (Table 1). The innovative aspect of this research is to identify recurring and unique locations using GPS data, and PA levels associated with these locations for 6-hour time-windows. The time variation of PA over the duration of a week showed similar PA patterns during the four 6-hour time-windows (Table 1 and Supplementary Figure 1), indicating that individuals may be performing specific activities at certain time-windows. This information can be further utilized to create personalized interventions based on individuals' needs, location, and time-windows. PerPAL is a model that bridges research to practice. If research can demonstrate that specific locations are consistently associated with different levels of physical activity, practitioners can support consumers to use their environment and desired community participation to increase PA (Vancampfort et al., 2016).

References

Adams, M.A., Todd, M., Kurka, J., Conway, T.L., Cain, K.L., Frank, L.D., Sallis, J.F., 2015. Patterns of walkability, transit, and recreation environment for physical activity. American Journal of Preventive Medicine 49(6), 878-887.

Birant, D., Kut, A., 2007. ST-DBSCAN: An algorithm for clustering spatial–temporal data. Data & Knowledge Engineering 60(1), 208-221.

Brusilovskiy, E., Klein, L.A., Salzer, M.S., 2016. Using Global Positioning Systems to Study Health-Related Mobility and Participation. Social Science & Medicine 161, 134-142.

Carlson, J.A., Jankowska, M.M., Meseck, K., Godbole, S., Natarajan, L., Raab, F., Demchak, B., Patrick, K., Kerr, J., 2015. Validity of PALMS GPS scoring of active and passive travel compared with SenseCam. Medicine and Science in Sports and Exercise 47(3), 662-667.

Schoggen, P., 1989. Behavior settings: A revision and extension of Roger G. Barker's ecological psychology. Stanford University Press.

Stubbs, B., Williams, J., Gaughran, F., Craig, T., 2016. How sedentary are people with psychosis? A systematic review and meta-analysis. Schizophrenia Research 171(1-3), 103-109.

Townley, G., Brusilovskiy, E., Snethen, G., Salzer, M.S., 2018. Using geospatial research methods to examine resource accessibility and availability as it relates to community participation of individuals with serious mental illnesses. American journal of community psychology 61(1-2), 47-61.

Vancampfort, D., De Hert, M., De Herdt, A., Bosch, K.V., Soundy, A., Bernard, P.P., De Wachter, D., Probst, M., 2013. Associations between physical activity and the built environment in patients with schizophrenia: a multi-centre study. General hospital psychiatry 35(6), 653-658.

Vancampfort, D., De Hert, M., De Herdt, A., Soundy, A., Stubbs, B., Bernard, P., Probst, M., 2014. Associations between perceived neighbourhood environmental attributes and self-reported sitting time in patients with schizophrenia: a pilot study. Psychiatry Research 215(1), 33-38.

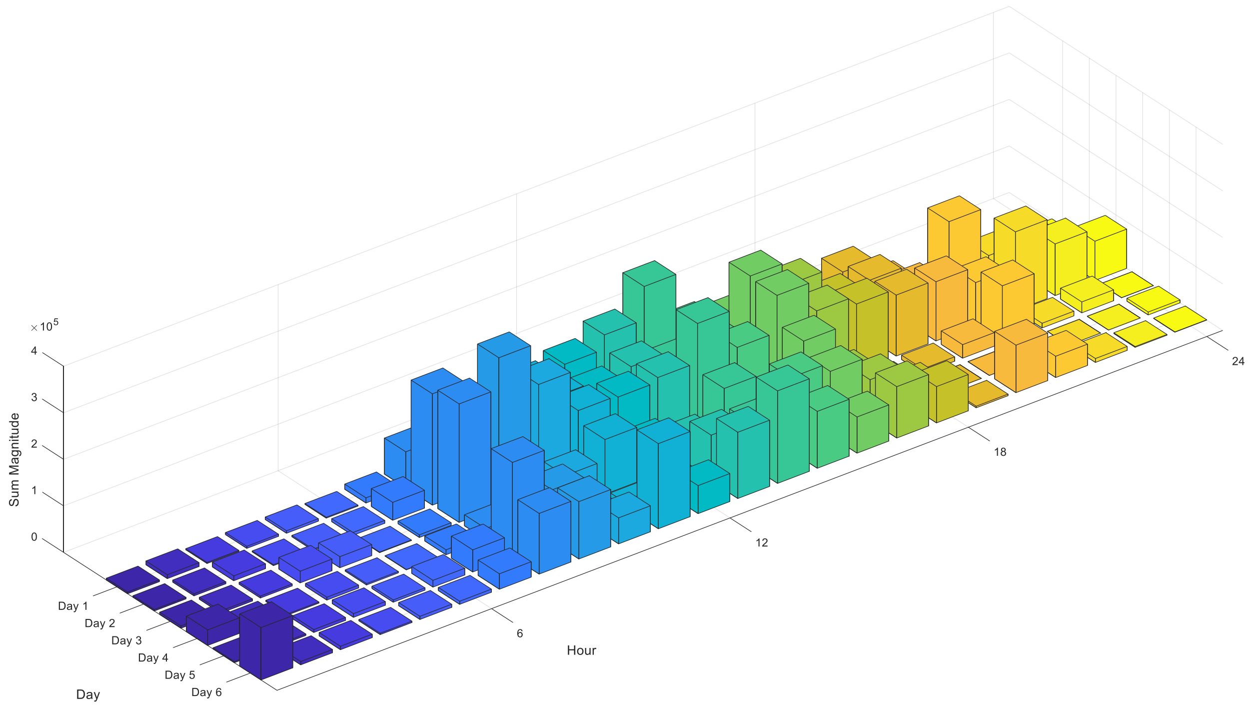
Vancampfort, D., Rosenbaum, S., Probst, M., Connaughton, J., du Plessis, C., Yamamoto, T., Stubbs, B., 2016. What are the top 10 physical activity research questions in schizophrenia? Disability and rehabilitation 38(22), 2235-2243.

Table

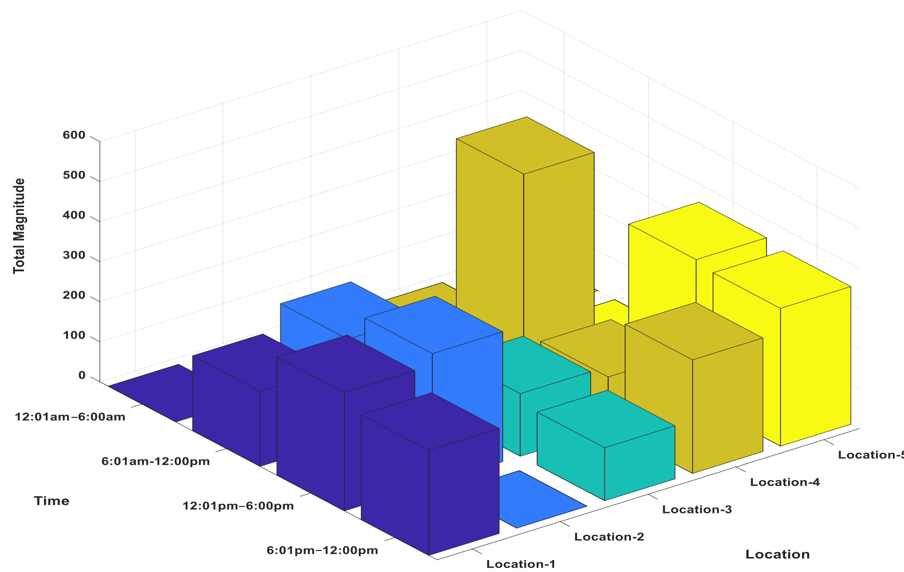
Table 1: PA levels associated with various locations and 6-hour time-windows during baseline and follow-up testing sessions for each of the participants.

Participant ID		12:01 am – 6:00 am		6:01 am – 12:00 pm		12:01 pm – 6:00 pm		6:01 pm – 12:00 pm	
		Number of Locations	**PA**	**Number of Locations**	**PA**	**Number of Locations**	**PA**	**Number of Locations**	**PA**
1	Baseline	1	46.5	3	173.6	3	143.5	1	54.6
	Follow-up	1	49.0	3	129.9	3	127.1	1	87.8
2	Baseline	1	5.0	3	203.9	4	250.3	2	199.1
	Follow-up	1	14.7	2	175.2	3	294.3	1	199.9
3	Baseline	1	40.7	3	241.6	4	184.9	1	104.7
	Follow-up	1	35.5	4	214.4	4	163.4	1	100.9
4	Baseline	1	31.9	4	293.8	4	455.5	1	37.4
	Follow-up	1	36.5	4	340.7	4	467.4	2	299.9
5	Baseline	1	47.8	2	126.2	3	192.7	3	151.3
	Follow-up	1	61.9	2	195.3	3	222.7	3	161.3
6	Baseline	1	31.9	2	302.9	2	332.1	1	189.7
	Follow-up	1	8.9	2	339.5	1	336.7	1	230.2
7	Baseline	1	0.5	3	412.3	3	444.7	1	1.3
	Follow-up	1	0.4	3	318.9	2	356.3	1	1.2
8	Baseline	1	263.7	4	539.4	4	525.9	1	222.8
	Follow-up	1	165.2	3	477.4	4	488.8	1	170.7
9	Baseline	1	97.4	1	442.3	1	328.6	1	88.8
	Follow-up	1	81.0	1	359.6	1	287.0	1	89.6
10	Baseline	1	88.5	1	474.0	1	367.8	1	169.1
	Follow-up	1	140.1	1	412.6	1	375.9	1	181.7

Supplementary Figure



A



B

Supplementary Figure 1: (A) PA levels (y-axis) for a participant (ID #5) for one-hour time-windows during six days of testing. (B) PA levels for the same participant at four different locations (x-axis) over four time-windows (z-axis).

Supplementary Table

Supplementary Table 1: The performance of PerPAL models' prediction with respect to the actual PA levels measured during follow-up phase. Regression parameters for the linear models developed for each participant.

Participant ID	Correlation (R)	Variation (R^2)	Adjusted R^2	Standard Error of the Estimate	Significance (p)	Mean Error (SD) in %
1	0.99	0.99	0.98	10.58	0.00	-0.08 (5.3)
2	1.00	0.99	0.99	7.96	0.03	2.79 (21.2)
3	0.94	0.89	0.73	41.20	0.15	-0.29 (16.5)
4	0.96	0.94	0.91	54.99	0.00	2.95 (17.5)
5	0.89	0.80	0.69	41.81	0.03	-6.38 (30.0)
6	0.99	0.98	0.93	40.98	0.17	-1.15 (41.8)
7	0.99	0.99	0.98	32.86	0.01	-2.34 (9.0)
8	0.95	0.90	0.82	95.17	0.01	-0.52 (24.7)
9	0.99	0.99	0.99	7.96	0.03	-0.28 (2.3)
10	0.99	0.98	0.94	35.75	0.15	-0.56 (6.4)