

Evaluating a Potential Commercial Tool for Healthcare Application for People with Dementia

*^{1a} Tanvi Banerjee, ^{2a} Pramod Anantharam, ^{3c} William L. Romine, ^{4b} Larry Lawhorne, ^{5a} Amit Sheth

^aDepartment of Computer Science and Engineering, Wright State University

^bBoonshoft School of Medicine, Wright State University

^cDepartment of Biological Sciences, Wright State University

¹tanvi@knoesis.org, ²pramod@knoesis.org, ³william.romine@wright.edu, ⁴larry.lawhorne@wright.edu, ⁵amit@knoesis.org

Kno.e.sis Center, Department of Computer Science and Engineering, Wright State University
303 Russ Engineering Building, 3640 Colonel Glenn Highway
Dayton, Ohio 45435 USA

Abstract - *The widespread use of smartphones and sensors has made physiology, environment, and public health notifications amenable to continuous monitoring. Personalized digital health and patient empowerment can become a reality only if the complex multisensory and multimodal data is processed within the patient context, converting relevant medical knowledge into actionable information for better and timely decisions. We apply these principles in the healthcare domain of dementia. Specifically, in this study we validate one of our sensor platforms to ascertain whether it will be suitable for detecting physiological changes that may help us detect changes in people with dementia. This study shows our preliminary data collection results from six healthy participants using the commercially available Hexoskin vest. The results show strong promise to derive actionable information using a combination of physiological observations from passive sensors present in the vest. The derived actionable information can help doctors determine physiological changes associated with dementia, and alert patients and caregivers to seek timely clinical assistance to improve their quality of life.*

Keywords: Gerontechnology, activity monitoring, eldercare, patient monitoring, smart sensing

1 Introduction

Alzheimer's disease affects more than 5 million people claiming over 500,000 Americans annually [1]. As the sixth leading cause of death in Americans [1], its management is challenging. Current reactive healthcare costs more than 17% of GDP in the US [3, 4]. Alzheimer's related healthcare costs alone are around \$150 billion a year to Medicare and Medicaid [1]. To add to the challenge, dementia is an umbrella term that encompasses various forms of the disease such as Alzheimer's disease, vascular dementia, and

Huntington's disease, to name a few [2]. Not only are the healthcare costs associated with dementia staggering, but the impact on the caregivers is also a critical challenge; in 2013, 15.5 million family and friends provided 17.7 billion hours of unpaid care to those with Alzheimer's and other forms of dementia – care valued at \$220.2 billion [1]. With the exponential rise of the older population due to the baby boomers, the number of people with Alzheimer's disease (the most prevalent form of dementia) is estimated to reach around 13.8 million [1,6]. This creates the strong need for unobtrusive sensing modalities that can help monitor people with dementia and support caregivers.

With increasing adoption of mobile devices and low-cost sensors, an unprecedented amount of data is being collected [5]. However, in the context of dementia, it is challenging to convert this huge amount of data into actionable information that can: a) help detect behavioral changes in an individual with dementia and b) provide relevant information to the clinician supporting them in treating chronic illness. In our previous work, we derived actionable information from physical and physiological data collected from children diagnosed with asthma. We have developed kHealth kit [9, 28] a semantics-enabled smart mobile application with sensors, to capture observations from machine sensors (quantitative) and people (qualitative) in the domain of asthma [30]. We also have active clinical collaborations to investigate and evaluate the use of kHealth technology for reducing readmission of GI (gastrointestinal) and ADHF (acute decompensated heart failure) patients after their discharge from the hospital.

This paper reports our investigation to validate the sensors that will be used for the purpose for our ongoing study of physiological and behavioral markers of dementia. Using these markers, we aspire to build a model to detect changes in dementia patients and eventually attempt to predict adverse events. Specifically, we describe our preliminary work in

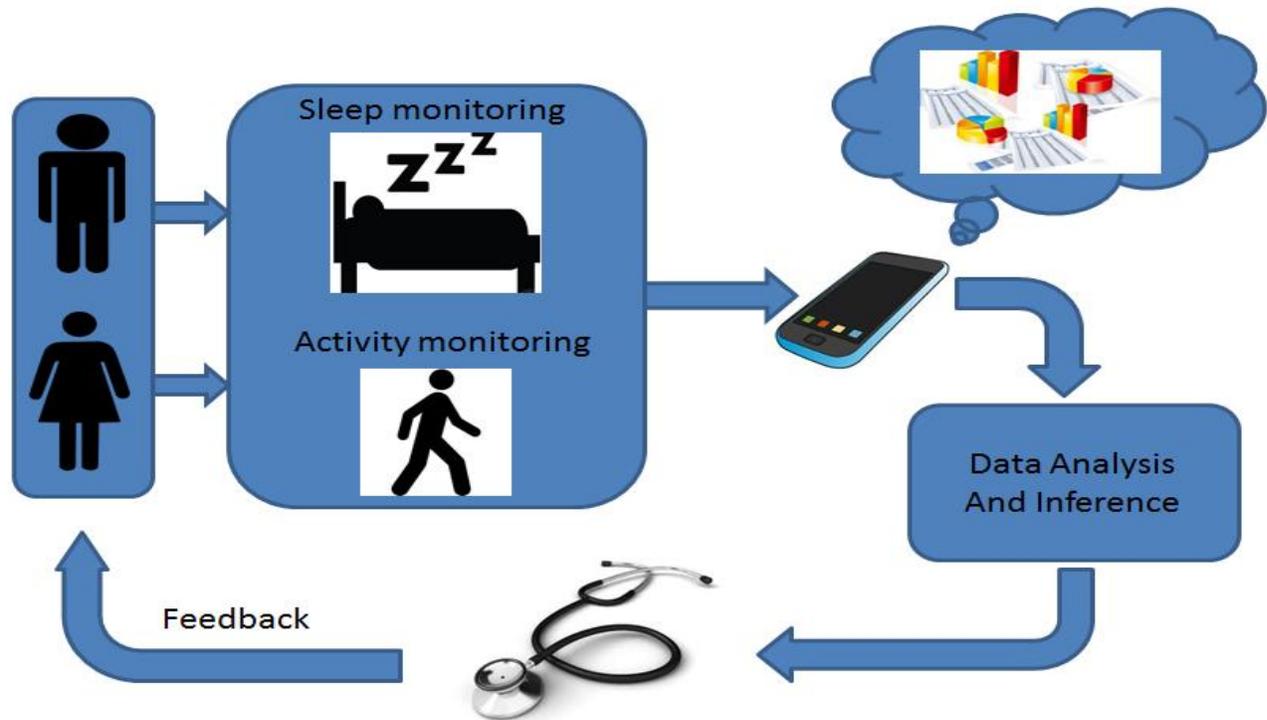


Figure 1. The kHealth Dementia application will measure physiological signals from the person with dementia as well as the caregiver to provide a deeper understanding of the behavior changes contributing to dementia

validating the parameters extracted from one of the most popular wearable sensors, Hexoskin, from Carre Technologies [7]. The Hexoskin system contains cardiac sensors, breathing sensors, and accelerometers that can be used to monitor movement, heart rate, and breathing in real-time [8]. Using this wearable technology, physiological parameters can be computed in a continuous and unobtrusive way. In this study, we analyze the data for six participants with varying demographics and discuss our results. Our analysis provides crucial insights into the physiological changes associated with dementia as well as analyze the temporal behavior of the patient. These insights can help clinicians diagnose and treat the illness and improve health management for the patients.

2 Related Work

The availability of low-cost sensors and mobile devices for monitoring physiological, physical, environmental, and cognitive health — within human bodies [10], on humans [11] and around humans [12] — are revolutionizing healthcare [13]. Microsoft Kinect and on-board sensors on mobile phones are being increasingly adopted in assisted living environments [14] and hospitals [15] for monitoring activities of daily living.

This trend is sure to accelerate with increasing FDA certification of devices or Internet of Things. With the rise of baby-boomers in the recent times, there has been an increase in research with Alzheimer’s patients. In [16], the researchers conducted a study to compare the gait parameters for

dementia patients and older adults without dementia using a single waist-worn accelerometer. The results were promising; however, it may be difficult for a person with dementia to wear an accelerometer unless properly concealed. In other gait extraction methods, researchers tested gait parameters extracted using the Microsoft Kinect to validate the sensor data [17].

In recent work on Ambient Assisted Living (AAL) technologies, there has been a strong interest in commercially available sensors. Studies such as [18] have highlighted the potential for commercial sensors, including the Hexoskin vest as remote monitoring technologies that can help detect behavioral changes in older adults. However, there needs to be an assessment of the instrument before testing the sensor with dementia patients. In a recent study [23], the Hexoskin was used as a sensor to test the quality index of the ECG signal from the heartrate sensor. However, there was no evaluation of the parameters extracted from the sensor or instrument validation for the data obtained from the Hexoskin. There is also an unpublished work using the heartrate, breathing rate and activity sensors from the Hexoskin at [27]. However, there was no evaluation of the cadence parameter, nor exploration of the parameter relationships in the study that is essential before using this sensing modality for longitudinal studies in healthcare domains like dementia.

In this work, we present a systematic study and a much deeper understanding of various physiological observations collected from Hexoskin. We demonstrate the feasibility of

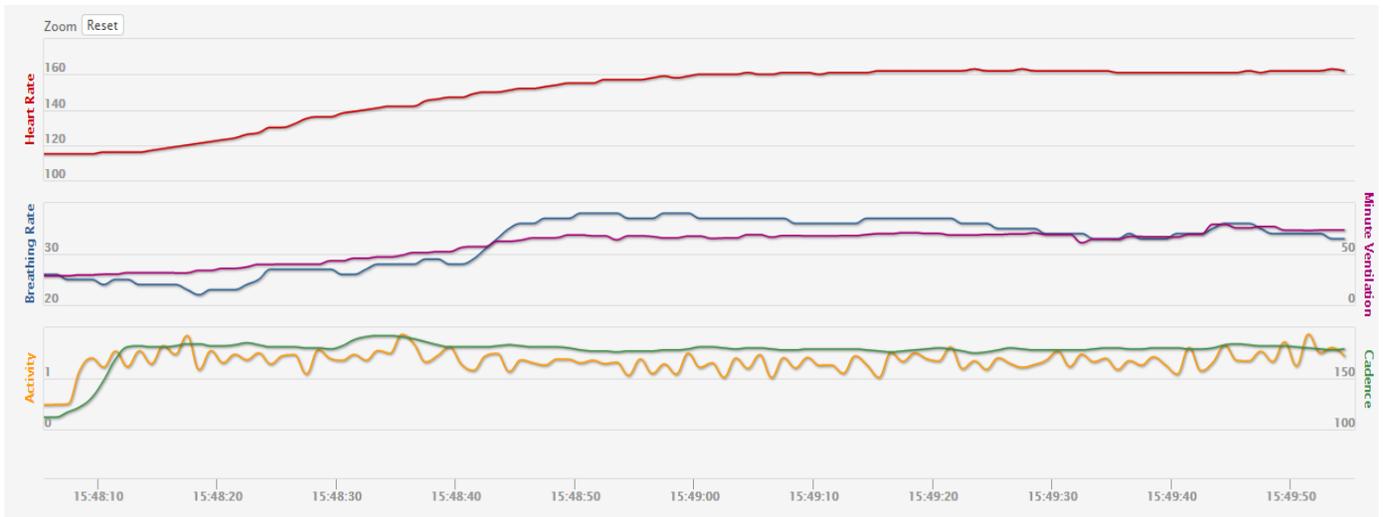


Figure 2. The Hexoskin data for a Run sequence showing the HR (top red), BR (blue middle), and A (yellow bottom) signals are labeled with the Y Axis on the left, and MV (purple middle), and C (green bottom) signals labeled with the Y Axis on the right. The X Axis represents time in the format hour : minute : second.

using insights gained by the analysis of physiological observations in dementia management.

3 Experiments and Analysis

In this section, we will discuss our proposed system setup for monitoring people with dementia. In the proposed plan of study, we hope to study the behavior of both the person with dementia as well as the caregiver. In the neuropsychiatric inventory study by Cummings [19], greater cognitive impairments were reported for people with dementia over time. The symptoms include agitation, apathy, depression, aberrant motor behavior, and abnormal nighttime behavior. Moreover, the deterioration in patient behavior and personality increases the stress on caregivers and leads to negative outcomes which need to be monitored to ensure that the caregiver can sustain his or her role to provide support to the person with dementia [20]. By continuous, unobtrusive monitoring of the physiological parameters of the person with dementia as well as the caregiver, we can detect changes in the movement and sleep patterns of the patient as well as the stress generated on the caregiver that are useful indicators for clinicians. Figure 1 shows the overall block diagram of our proposed approach. Commercially available sensors will be used to monitor both patients and caregivers, a daily questionnaire based on the Zarit Burden Interview questions [22] will be routinely asked to the caregiver using a mobile application to provide ground truth. We utilize statistical and machine learning approaches to extract behavioral patterns of the patients so that we can detect anomalies that can be used to predict behavioral disturbances in people with dementia. This information can then be provided to the clinician for further action on their part.

As mentioned earlier, one of the most promising sensors to monitor the patient is the Hexoskin vest. This measures five parameters: heart rate (HR) in beats per minute (BPM), breathing rate (BR) in BPM, minute ventilation (MV) to detect the volume of gas inhaled or exhaled by the lungs in lungs per minute (LPM), cadence (C), as well as the activity level (A) on a scale of 0 to 1 using accelerometers in the X, Y, and Z directions (resolution of 0.004g) [7]. We can see a sample of the data extracted using the Hexoskin in Figure 2. Figure 2 shows an example of a Run activity. We can see that the HR increases gradually over time during the participant’s activity as we would expect. Similarly, we see an expected increase in the other parameters over time as the person’s C, A, BR, and MV rises over time. This corroborates our understanding of the Run activity. We will look at a more in-depth statistical analysis of the parameters in Sections 3.1 and 3.2.

As compared to other commercially available sensors, this has the added benefit of being worn as an under shirt by the person with dementia, instead of wearable bracelets like the Fitbit [21] that could confuse the patient who could then possibly take it off. Moreover, the Hexoskin vest is Bluetooth enabled with over 14 hours of battery life and can locally store more than 150 hours of recording [7]. We will now discuss our instrument validation for the cadence measurement of the vest in Section 3.1.

3.1 Cadence Validation in a Controlled Setting

In this subsection, we first validate the C (cadence) parameter since there is a direct relationship between the gait related activities mentioned above with cadence. Moreover, studies such as [16] highlight the importance of gait-based features in differentiating between people with dementia and people without. For this validation, there were four

participants, two male and two female, between the ages 30-35. Data were captured in a controlled method with each participant asked to sit for ten minutes, walk for ten minutes, run at their normal pace for ten minutes, and run hard (sprint) for one minute. Figure 3 shows the box plots for the C parameter for the four participants for the four activity states. As we can see from Figure 3, the fitness across the four participants varies; especially for the Run and Sprint activity states. As can be expected, the cadence value is zero for all four participants at rest. Moreover, we can see the variance for the different individuals varies for the different activity states. For example, Subject 2 has much lower variance for the Sprint activity state whereas Subject 4 has a high variance for the same activity state. We also see that there are several outlier values for the Run and Sprint activity states for Subject 1. This was due to the participant walking for very short intervals during the data recording.

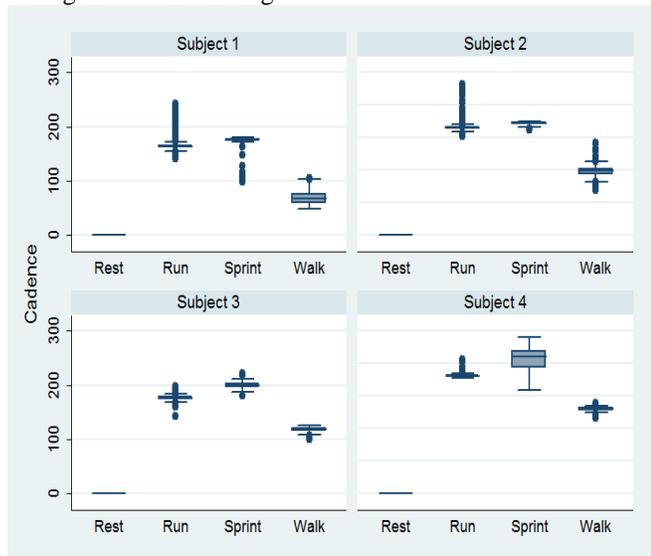


Figure 3. Box plots for Cadence (C) for the four participants in the controlled setting for the different activity states.

Table I shows the average C values and the standard deviation across the four participants for the Rest, Walk, Run, and Sprint activity states. Table I and Figure 3 collectively show the expected result that:

$$C_{\text{Rest}} < C_{\text{Walk}} < C_{\text{Run}} < C_{\text{Sprint}}$$

Table I. Cadence (C) Mean and Standard Deviation Results across Subjects for the Different Activity States

| Activity State | Mean | Std. Dev |
|----------------|--------|----------|
| Rest | 0.00 | 0.00 |
| Walk | 103.05 | 25.03 |
| Run | 171.95 | 10.25 |
| Sprint | 185.93 | 22.00 |

Using minimum norm quadratic estimation (MINQUE) [29], we explored the intra-class correlations of subject, activity state, and their interaction, with the data. We found that a majority (95.5%) of the variation in the parameter C can be explained by activity state while only 1.8% of the variation can be explained directly by differences between the subjects. 2.0% of the variation in cadence can be explained by individual differences in cadence between activity states. This leaves only 0.7% of the variation in cadence unexplained by Subject and Activity State. This indicates that the activity state affects the variance of C much more than differences in subjects or random error.

In summary, we find that differences in cadence between activity states are aligned with expectations. Further, we find that a vast majority of the variation in cadence can be explained by differences between subjects and activity states. These findings collectively support the precision and utility of the Hexoskin’s C parameter for detecting changes in activities across individuals.

3.2 Physiological Parameter Evaluation in Semi-Controlled Setting

In this study, we evaluate the performance of all the parameters extracted from the Hexoskin: HR, BR, MV, C, as well as A. Six participants were asked to perform walks in semi-structured settings in accordance with their comfort level. The participants ranged from ages 30 – 65 and were all healthy adults. Two were female and the remaining four were male participants. As mentioned earlier, the only requirement was that the participants perform some gait-related activities according to their comfort level. This involved walking around the house, inside the house, performing household chores, as well as sitting and resting. Data were recorded for approximately 26 hours for this experiment. Since we validated the C parameter in Section 3.1, we will use this as the key measure to evaluate the performance of the remaining physiological parameters.

3.2.1 Multivariate Analysis

In this subsection, we describe our results on the multivariate analysis of variance (MANOVA) with cadence (C) as the independent variable (IV) and the remaining parameters (A, MV, BR, HR) as the dependent variables (DV). In this way, we can see the effect of C on the remaining parameters as a whole instead of separately, as we see the individual relationships between the parameters in Section 3.2.2 [24]. We use the F-statistic calculated from Wilk’s Lambda as a multivariate criterion [25] for statistical significance of C as a predictor of the other parameters together ($\alpha = 0.05$) for each subject. Partial η^2 is used as a measure of the percentage of variance in the DV’s explained by C.

Table II. MANOVA results with C as IV and HR, BR, A, and MV as DV.

| MANOVA | Lambda | F* | Partial η^2 |
|-----------|--------|----------|------------------|
| Subject 1 | 0.128 | 28922.56 | 0.871 |
| Subject 2 | 0.160 | 26888.12 | 0.839 |
| Subject 3 | 0.181 | 32369.65 | 0.818 |
| Subject 4 | 0.255 | 3275.61 | 0.744 |
| Subject 5 | 0.375 | 8020.30 | 0.624 |
| Subject 6 | 0.242 | 6354.81 | 0.757 |

*Significant at $\alpha \ll 0.001$, p-value ~ 0

As we can see in Table II, cadence is a highly significant predictor of the DV's in all subjects (since the p-value is ~ 0 for all the six participants). Moreover, C explains between 62% - 87% of the variance for all the DVs across the six participants (as can be seen from the Partial η^2 values). Since cadence is a direct measure of activity state, it makes sense that parameters associated with heart rate, respiration, and activity will be highly related to cadence. Specifically, it is an expected finding that as C increases, the subject's oxygen demand is going to increase, which will in turn result in an increase in breathing and heart rates. Positive correlations can be used as evidence that the Hexoskin is working as expected, and is taking valid measurements. Now that we have looked at the variance analysis for these physiological parameters as a group, we explore the individual correlations in the following section.

3.2.2 Correlations between parameters

In this subsection, we will look at the relationship between the five parameters from the Hexoskin sensor. Table III shows the average Pearson correlation [26] between the five parameters across the six participants. The parameters significant at 95% confidence interval are highlighted in bold.

Table III. Average Pearson Correlation Results between the Five Parameters across the Six Participants.

| | Mean | Std. Dev | SE | $T_{df=5}$ | P-value |
|--------------|-------------|-------------|-------------|-------------|---------------|
| C-BR | 0.54 | 0.20 | 0.08 | 6.53 | 0.001* |
| C-HR | 0.16 | 0.28 | 0.12 | 1.38 | 0.226 |
| C-MV | 0.66 | 0.15 | 0.06 | 10.9 | 0.000* |
| C-A | 0.85 | 0.07 | 0.03 | 28.9 | 0.000* |
| BR-HR | 0.18 | 0.28 | 0.11 | 1.56 | 0.180 |
| BR-MV | 0.18 | 0.21 | 0.09 | 2.04 | 0.097 |
| BR-A | 0.52 | 0.18 | 0.07 | 7.06 | 0.001* |
| MV-HR | 0.31 | 0.28 | 0.11 | 2.75 | 0.040* |
| MV-A | 0.64 | 0.18 | 0.07 | 8.93 | 0.000* |
| HR-A | 0.19 | 0.28 | 0.11 | 1.69 | 0.152 |

*Significant at $\alpha = 0.05$

As we can see, six of the parameter pairs show a strong correlation at the 0.05 level. The parameter HR shows the least correlation among the parameters. It is the least significant predictor for cadence across the six participants. Many factors could lead to this: the different body shapes and sizes may lead to different placements of the heart sensor across the participants that could lead to an error in measurement. HR varies across subjects based on the fitness level and HR can change due to stress or caffeine intake (observed with one of our participants), which has no relationship with C. Also, since a person's heart is always beating (at varying levels) even when at rest, the HR value does not change as much as the other parameters when the person's C or A increases; leading to lower correlation. This could specifically be the case for the Walk activity since the HR parameter may not increase significantly. However, we find that the BR and MV parameters exhibit more variation with C; these show strong potential to complement C and A in the detection of behavior patterns.

4 Acknowledgement

We thank Wright State University's Vice President for Research for the partial funding of this effort. We also thank Vaikunth Sridharan for supporting kit preparation and all the participants of our study for collecting real-world data for our analysis.

5 Conclusions

We tested and validated the sensor data extracted from the Hexoskin vest. We first validated cadence using different activity states of rest, walk, run, and sprint in a controlled setting. We then evaluated the performance of the other parameters in a semi-controlled environment using six participants from a more diverse age group. The parameters BR, MV, and A were found to be consistent with the C values. These show strong potential to differentiate between different activity and behavior patterns. This shows that all parameters except for HR may be directly useful in detecting changes in patient behavior for future studies. Even the HR sensor may be a useful parameter if we look at other features like temporal differences spikes in HR. We plan to explore these temporal trends in our future experiments.

We build on kHealth's foundation to test our hypothesis that an evidence-based approach can help doctors determine more precisely the changes in behavior patterns for people with dementia. All our kHealth applications involve active clinical collaborations with medical professionals leading to evaluation with patients. Our next step is to test the system using participants with dementia. The Hexoskin has shown strong promise as a sensor platform for detecting changes in activity and behavioral patterns. Additional research is needed to study the efficacy of these physiological parameters as predictors for behavioral change in people with dementia. We can then develop a precise understanding of these effects in

dementia patients in order to quantify the sensed data's role for clinical assessment of their symptoms. The derived understanding can be used to alert caregivers and physicians so that appropriate measures can be taken to ensure the safety and well being of both the people with dementia, as well as the caregivers.

References

- [1] Alzheimer's Association description of Alzheimer's statistics, Available online at: http://www.alz.org/alzheimers_disease_facts_and_figures.asp#quickFacts
- [2] Dementia related facts, Available online at: <http://www.cdc.gov/mentalhealth/basics/mental-illness/dementia.htm>
- [3] D. A. Squires, "The U.S. Health System in Perspective: A Comparison of Twelve Industrialized Nations," June 2011, Available online at: <http://bit.ly/oZwhFZ>
- [4] Health Costs: How the U.S. Compares With Other Countries, Available online at: <http://www.pbs.org/newshour/rundown/2012/10/health-costs-how-the-us-compares-with-other-countries.html>
- [5] Quantified Self <http://quantifiedself.com/>
- [6] G. K. Vincent, V. A. Velkof, "The next four decades: The older population in the United States: 2010 to 2050." Washington, D.C.: U.S. Census Bureau; 2010.
- [7] Hexoskin. www.hexoskin.com
- [8] A. Pasolini, "Sensor-packed Hexoskin shirt measures performance in real time". Available at: <http://www.gizmag.com/hexoskin-sensor-t-shirt-body-metrics/29098/> Gizmag, September 19, 2013.
- [9] kHealth: A knowledge-enabled semantic platform to enhance decision making and improve health, fitness, and well-being, Available online at: <http://knoesis.org/projects/khealth> (Accessed May 27, 2013).
- [10] V. Santhisagar, T. Ioannis, B. Diane, J. C. Faquir, P. Fotios, "Emerging synergy between nanotechnology and implantable biosensors: A review." *Biosensors and Bioelectronics* 25.7: 1553-1565, 2010.
- [11] J. S. Karlsson, U. Wiklund, L. Berglin, N. Östlund, M. Karlsson, T. Bäcklund, & L. Sandsjö, "Wireless monitoring of heart rate and electromyographic signals using a smart T-shirt." In *Proceedings of International Workshop on Wearable Micro and Nanosystems for Personalised Health*, 2008.
- [12] M. Chan, E. Campo, D. Estève, & J. Y. Fourniols, "Smart homes—current features and future perspectives." *Maturitas*, 64(2), 90-97, 2009.
- [13] E. Topol, "The creative destruction of medicine: How the digital revolution will create better health care." *Basic Books (AZ)*, 2012.
- [14] T. Banerjee, M. Skubic, J. M. Keller & C. C. Abbott, "Sit-To-Stand Measurement For In Home Monitoring Using Voxel Analysis," *IEEE Journal of Biomedical and Health Informatics*, 18(4):1502-1509, 2014.
- [15] T. Banerjee, M. Rantz, M. Li, M. Popescu, E. Stone & M. Skubic, "Monitoring Hospital Rooms for Safety Using Depth Images," *Proceedings, AAAI Fall Symposium Series - AI for Gerontechnology*, Washington DC, November 2-4, 2012.
- [16] M. Gietzelt, K. H. Wolf, M. Kohlmann, M. Marschollek, and R. Haux. "Measurement of Accelerometry-based Gait Parameters in People with and without Dementia in the Field." *Methods Inf. Med* 52, no. 4: 319-325, 2013.
- [17] E. Stone & M. Skubic, "Evaluation of an Inexpensive Depth Camera for In-Home Gait Assessment," *Journal of Ambient Intelligence and Smart Environments*, 3(4):349-361, 2011.
- [18] A. L. Bleda, R. Maestre, A. J. Jara, & A. G. Skarmeta, "Ambient Assisted Living Tools for a Sustainable Aging Society." In *Resource Management in Mobile Computing Environments* pp. 193-220. Springer International Publishing, 2014.
- [19] J. L. Cummings, "The Neuropsychiatric Inventory: Assessing psychopathology in dementia patients." *Neurology* 48 (Supple 6): S10-S16, 1997.
- [20] W. E. Haley, E. G. Levine, S. L. Brown, and A. A. Bartolucci. "Stress, appraisal, coping, and social support as predictors of adaptational outcome among dementia caregivers." *Psychology and aging* 2, no. 4: 323, 1987.
- [21] Fitbit sensor. www.fitbit.com
- [22] S. H. Zarit, K. E. Reever, J. Bach-Peterson, "Relatives of the impaired elderly: correlates of feelings of burden." *Gerontologist*. 20:649-55, 1980.
- [23] D. Tobon Vallejo, T. Falk, M. Maier, "MS-QI: A Modulation Spectrum-Based ECG Quality Index for Telehealth Applications," *Biomedical Engineering, IEEE Transactions on*, 2015.

- [24] R. T. Warne, "A primer on multivariate analysis of variance (MANOVA) for behavioral scientists". *Practical Assessment, Research & Evaluation* 19 (17): 1–10, 2014.
- [25] K. V. Mardia, J. T. Kent, J. M. Bibby, "Multivariate Analysis." Academic Press, 1979.
- [26] J. Schmid Jr., "The Relationship between the Coefficient of Correlation and the Angle Included between Regression Lines". *The Journal of Educational Research* 41 (4), 1947.
- [27] Hexoskin data validation. Available at: [https://cdn.shopify.com/s/files/1/0284/7802/files/CSEP_Hexoskin_Poster - University of Waterloo.pdf?11148](https://cdn.shopify.com/s/files/1/0284/7802/files/CSEP_Hexoskin_Poster_-_University_of_Waterloo.pdf?11148)
- [28] A. Sheth, P. Anantharam, K. Thirunarayan, "kHealth: Proactive Personalized Actionable Information for Better Healthcare," *Workshop on Personal Data Analytics in the Internet of Things (PDA@IOT 2014), collocated at VLDB 2014*, Hangzhou, China, September 5th 2014.
- [29] C.R. Rao. "Estimation of variance and covariance components in linear models." *Journal of the American Statistical Association*, 67(337), 112-115, 1972.
- [30] P. Anantharam, T. Banerjee, A. Sheth, K. Thirunarayan, S. Marupudi, V. Sridharan, S. G. Forbis, "Knowledge-driven Personalized Contextual mHealth Service for Asthma Management in Children", *IEEE 4th International Conference on Mobile Services*, June 27 - July 2, 2015, New York, USA