Capturing Behavioral Biomarkers to Guide Personalized Treatment

Marjorie Skubic, IEEE Senior Member, Marilyn Rantz, IEEE Member, Steve Miller, and Kathryn Musterman

Abstract— **Embedded health assessment using in-home sensors is being tested in TigerPlace, a 54-unit senior housing site that supports aging in place. We present case studies of TigerPlace residents which illustrate how behavioral biomarkers from in-home sensors can be used to personalize treatment.**

I. Introduction

We have tested embedded health assessment in TigerPlace using in-home sensors. The system functions as a clinical decision support system that generates health change alerts [1]. A bed sensor captures quantitative pulse, respiration, restlessness and sleep patterns [2]. A gait analysis system using a depth camera estimates walking speed, stride time, and stride length by observing walking paths in the home [3]. Motion sensors capture room to room movement and overall activity level. Smart algorithms generate health alert emails based on changing patterns in the sensor data. Alerts are sent to clinical staff, who determine whether an intervention is warranted. Each health alert includes embedded links to a web interface for visualizing sensor data trends and a feedback interface to rate the clinical relevance of the alert.

II. Case Studies

Our experience has shown how the sensor system can be used to capture new vital signs in the form of behavioral biomarkers that offer the opportunity for treatment interventions that target the needs of the individuals. Here, we present several case studies to illustrate the point.

Eva was an 88 year old woman who had established a cycle of re-hospitalizations due to congestive heart failure, as her condition worsened, improved, and then worsened again. During a period at home, the in-home sensors captured a changing night time pattern in which Eva left her bed within an hour of going to bed and spent the rest of the night in her recliner chair. Based on this changing pattern, nursing staff evaluated Eva and determined that she needed a medication change due to her chronic heart failure. However, she had not gained enough weight to satisfy the standard protocol for a medication change. Through persistent communication with Eva's physician, her medication was changed, and Eva never went back to the hospital for heart failure again. In total, Eva lived in her apartment for over 5 years.

Ginger was a 76 year old woman with Parkinson's disease, who had a history of falls. The in-home sensors allowed Ginger to stay in her apartment due to the active fall detection feature [4]. Her falls were promptly detected, generating alerts, so that she could get immediate help. The depth camera system produced shadowy silhouettes of the motion so that the falls could be examined; the data capture showed that she mostly fell on her right side and many falls occurred during transfer to/from the wheelchair. A physical therapist was brought it to explore interventions; one suggestion was to use a different type of wheelchair. The sensors were also used to determine that she had difficulties controlling her electric wheel chair within the cluttered apartment environment; this was partially disabled for safety reasons. With this monitoring, Ginger was able to stay in her apartment for over 8 years.

Another example is a couple; Mrs. Smith had Parkinson's disease, and Mr. Smith was thought to be healthy. Through the in-home monitoring, the sensors showed pertinent patterns that affected the couple's treatment. First, Mrs. Smith's gait pattern was stable; her medication regimen was working. However, Mr. Smith's walking speed declined, due to his shorter footsteps. Around the same time, the sensors showed unusual interactions between the couple, such that it appeared Mr. Smith might be causing Mrs. Smith's falls. This prompted a further investigation which showed Mr. Smith's cognitive decline. With this diagnosis, the intervention strategy changed significantly.

These cases illustrate how behavioral data from in-home sensors can be used effectively to plan personalized treatment for older adults, to help maintain function and independence as long as possible. Currently, the system relies on the expertise of clinical staff to interpret the alerts. For scaled up use, we recommend further development on alert algorithms and interfaces to help consumers use the system directly.

M. Skubic is with the Electrical & Computer Eng. Dept., University of Missouri, Columbia, MO 65211, USA (phone: 573-882-7766; e-mail: skubicm@missouri.edu).

M. Rantz, S. Miller & K. Musterman are with the Sinclair School of Nursing, University of Missouri, USA (e-mail: rantzm@missouri.edu; millerst@missouri.edu; mustermank@missouri.edu).

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References

[1] M. Skubic, R.D. Guevara and M. Rantz, "Automated Health Alerts Using In-Home Sensor Data for Embedded Health Assessment," *IEEE J of Trans Eng in Health and Medicine*, 2015, vol. 3, pp.1-11.

[2] D. Heise, L. Rosales, M. Sheahen, B.Y. Su and M. Skubic, "Non-Invasive Measurement of Heartbeat with a Hydraulic Bed Sensor: Progress, Challenges, and Opportunities," *Proc, IEEE Intl. Instr & Meas Tech Conf*, Minneapolis, May, 2013, pp 4356-4360.

[3] E. Stone and M. Skubic, "Unobtrusive, Continuous, In-Home Gait Measurement Using the Microsoft Kinect," *IEEE Trans on Biomed Eng*, 2013, vol. 60, no. 10, pp.2925-2932.

[4] E. Stone and M. Skubic, "Fall Detection in Homes of Older Adults Using the Microsoft Kinect," *IEEE J of Biomed and Health Informatics*, 2015, vol. 19, no. 1, pp. 290-301.