A Framework for Harmonizing Sensor Data to Support Embedded Health Assessment

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Abstract— **The use of in-home and mobile sensing is likely to be a key component of future care and has recently been studied by many research groups world-wide. Researchers have shown that embedded sensors can be used for health assessment such as early illness detection and the management of chronic health conditions. However, research collaboration and data sharing have been hampered by disparate sets of sensors and data collection methods. To date, there have been no studies to investigate common measures that can be used across multiple sites with different types of sensors, which would facilitate large scale studies and reuse of existing datasets. In this paper, we propose a framework for harmonizing heterogeneous sensor data through an intermediate layer, the *Conceptual Sensor*, which maps physical measures to clinical space. Examples are included for sleep quality and ambulatory physical function.**

I. Introduction

In-home sensors hold enormous potential for identifying early changes in health, but scaling the research to make the critical link between sensor data and early health assessment will require a coordinated effort among multiple research groups. In this paper, we offer a framework for harmonizing heterogeneous sensor data across multiple sites to support embedded health assessment, that is, the assessment of health problems or health changes through opportunistic sensing mounted in the home or through wearable or mobile devices. Identifying and assessing health problems while they are nascent or even pre-symptomatic can provide a window of opportunity for interventions that can alleviate problems before they become catastrophic. However, there is a need for scaled up research studies to test the approach and better understand how to utilize embedded sensor data.

To date, there have been no studies to investigate common measures that can be used across multiple sites with potentially different types of sensors. One approach would be to standardize the sensors used, but that could eliminate the use of existing datasets, new, improved sensors as they become available, and invention of new technologies. Instead, we propose an intermediate layer between the physical sensors and the health and wellbeing assessments and outcomes that will harmonize the sensor data by providing common measures, supporting the sharing of datasets, and facilitating further study of the efficacy of embedded health assessment.

Joint standardization efforts in healthcare between the private and public sectors are underway in many areas (http://www.hitsp.org). Standards such as HL7 (http://www.hl7.org) provide a common framework for interoperability and communication between disparate systems, both on the individual sensor level, as well as how data and summaries are transmitted to electronic medical records. On the sensor and device level, the IEEE 11073™ is a family of standards for medical device interoperability. Seven parts were initially adopted on October 1, 2008 [1]. Part 10471, Independent Living Activity Hub, establishes a normative definition of communication between personal telehealth independent living activity hub devices and compute engines (e.g., cell phones, personal computers, personal health appliances, set-top boxes) in a manner that enables plug-and-play interoperability [2]. The Continuity of Care Document (CCD) is an XML-based markup standard intended to specify the encoding, structure and semantics of a patient summary clinical document for exchange. The Continuity of Care Record (CCR) is a core dataset of the most relevant clinical information about a patient's healthcare [3] that provides a format for forwarding the data to another entity to support the continuity of care.

In a similar way, we assert that harmonization among disparate sensor types with a link to the clinically relevant measures will propel collaboration and data sharing for large scale studies. In this paper, we first discuss barriers that discourage a common set of sensors for all and then present our proposed intermediate, conceptual sensor layer. Examples are provided for sleep quality and ambulatory physical function. We conclude with a discussion.

II. Barriers to a Common Set of Sensors

In-home and mobile sensing has been studied by many research groups world-wide for assessing health, safety, and wellbeing. However, each group has a different set of sensors, in part because they focus on different research questions or different target subjects. For example, consider the early detection of physical health problems that may

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require different approaches from those focused on cognitive health problems or mental health problems. All of these issues affect an elderly population but may require different types of assessment. Physical function may be assessed by capturing overall activity patterns (sedentary vs. active), walking gait patterns, sit to stand motions, sleep patterns, pulse and respiration [4]. Cognitive health assessment may use walking gait but also include assessment of activities of daily living (ADLs) [5], and interactive cognitive games on a computer [6]. Mental health assessment may use overall activity and sleep patterns as well as socialization via a phone or time out of the home [7]. Although there is some overlap, each condition may require a different optimal suite of sensors or different data processing methods.

Another target use of embedded health assessment is the management of chronic health problems, such as diabetes, arthritis, heart disease, or Parkinson's disease. The Parkinson's assessment might use computer usage as a proxy for the finger tapping test, while this might have little value for monitoring other chronic health problems. Researchers focusing on fall risk assessment need to consider parameters such as walking speed, stride time, and stride length, while this may not be important for someone with depression.

Other uses include safety and fall detection. There have been many sensing modalities proposed for fall detection, including wearable accelerometers [8], single cameras, multiple cameras [9], depth cameras [10], radar [11], and acoustic arrays [12]. Some work better than others, depending on the context of use. For example, wearable accelerometers do not work well if not worn consistently and recharged as necessary, which presents challenges for elderly users. Vision-based sensors work well for some environments but have failures in cluttered spaces with occlusions. Radar might not work as well in the open space but may be the best choice in tight spaces such as bathrooms because radar can penetrate structural elements. Each sensing modality has an uncertainty associated with it which can be measured against a gold standard. However, the uncertainty is also affected by the context in which the sensor is used.

Thus, there are a number of reasons why a fixed, common set of sensors is not practical: due to different research focus areas, different health conditions, different target users, and different environments in which the sensors are used. A fixed set of sensors also limits the possibility of using new sensors that might be available in the future and offer better performance. As a result, organizing large scale studies on embedded health assessment provides challenges. The heterogeneity of sensors and data types represents challenges to collaborative studies across organizations as well as to the development of generalizable algorithms. We, therefore, propose an intermediate layer, the *Conceptual Sensor*, to address these challenges.

III. THE CONCEPTUAL SENSOR LAYER

Our view of the conceptual sensor (CS) is an abstraction of the physical sensors that provides an intermediate connection to health and wellbeing assessments. Fig. 1 illustrates this mapping. From the physical sensors, the monitored metrics are translated into an intermediate layer that *harmonizes* the data into a set of common measures with known uncertainty for specific contexts of use. This approach facilitates data sharing across multiple sites and different sets of sensors. This set of common measures, the CS layer, can be used for large collaborative studies to investigate embedded health assessment. The uncertainty associated with each conceptual sensor, given a context of use, provides a characterization of this intermediate layer that allows generalization for embedded health assessment.

Other fields have benefitted from similar efforts, e.g., the logical sensor proposed in robotics [13]. However, there is an important distinction. Whereas the logical sensor is a mapping from physical measure to physical space, the proposed conceptual sensor is a mapping from physical measure to clinical space. Different CS data types must be supported, including numeric, qualitative or linguistic, binary, statistical, and state-driven models. A key motivator for logical sensors was to achieve dynamic reconfiguration to support fault tolerance. Although this will be useful for embedded health assessment, it is not our primary motivator. Our main goal is to share datasets and facilitate the medical efficacy of embedded health assessment.

Table I includes an example list of possible physical sensors which can be embedded to capture behavior and health. Table II displays categories of health and wellbeing that the clinicians on our research team (with expertise in gerontology) brainstormed and developed as clinically relevant; the common clinical uses are listed. This framework is similar to others proposed by gerontologists who are familiar with the seminal work of Lawton [14]. The harmonized measures of the CS can be hand-crafted. Uncertainty can be measured against a gold standard measurement, e.g., comparing walking speed from the Kinect depth images to a marker-based motion capture system or pulse rate from a bed sensor to a reference signal from a finger sensor. However, learning methods can also be used to produce harmonized measures and uncertainty, given a set of physical sensors and a usage context.

No single computational procedure or learning algorithm is expected to be able to address all CS problems due to the great diversity of the physical sensors and their respective uncertainty, such as functional, probabilistic, linguistic and state-based models. Several computational approaches are applicable, including clustering (unsupervised learning), multiple instance learning, fuzzy logic rule systems, learning fuzzy measures for fuzzy integrals, and learning human behavior using a group of learning automata, similar to a mixture of experts.

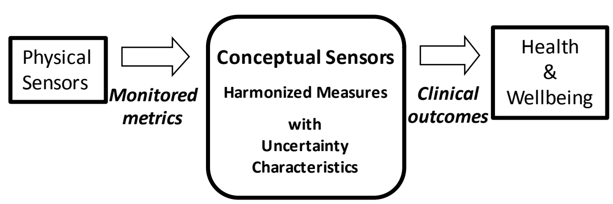

Fig. 1. The Conceptual Sensor is a mapping from physical measure to clinical space.

For example, clustering techniques can be used to explore the structure of the physical sensor data and its possible mappings to the CS space. Possible applications include (1) using cluster validity algorithms [15] for discovering which sets of monitored metrics to use and how many CS states exist; (2) analyzing intra- and inter-cluster variance with respect to state resolution (uncertainty) to determine CS precision; and (3) comparing partitions for temporal CS behavior analysis. In addition, clustering can be used to validate a set of hand-crafted CS's. For example, assume we want to explore a state-based model for a sleep quality CS by clustering the available data for a given time period produced by hydraulic and radar bed sensors. We first apply cluster validity algorithms to determine the number of clusters, C. Well-separated clusters might suggest that the sleep quality CS should have C states. Then, by comparing the clustering structures obtained for different time periods using partition comparison algorithms [16], we can assess the stability of the sensor and its time behavior. Hence, clustering as a means of unsupervised data analysis can have multiple roles from CS structure discovery to validating the quality of hand-crafted CSs according to the underlying patterns in physical sensor data.

IV. Conceptual Sensor Examples

For illustration, we provide two examples. Fig. 2 shows a sleep quality example, using various bed and motion sensors. Fig. 3 shows an example for ambulatory physical function; gait and other movement parameters can be captured with a variety of sensing systems. In both examples, a set of common clinical outcomes is used for health and wellbeing assessment. Again, clinicians on the research team brainstormed the clinical outcome measures and health and wellbeing clinical examples.

Consider the example given in Fig. 3. Walking speed has been measured with in-home sensors using a PIR array [17], Doppler radar [18], and Kinect depth images [19]. The first step in the development of a conceptual sensor is to define the phenomenon to be measured. In the case of a walking person, this may be the velocity of the center of mass of the walking individual derived from the trajectory observed over time. Once defined, lab experiments can be used to measure walking speed and possibly the motion direction with each sensor modality using models of the sensors. The resulting walking speed estimates can then be compared to a "gold standard", marker-based Vicon motion capture system. Since the Vicon system measures the position of each marker, it is necessary to build a model that estimates the center of mass velocity. This velocity over time represents the output of a conceptual sensor.

In addition to the measurement of the quantity of interest, it is necessary to capture the uncertainties associated with the measurements. Empirical results may show that, for unconstrained walking paths, the PIR array will have an uncertainty of ϵ_p, radar an uncertainty of ϵ_r, and the Kinect an uncertainty of ϵ_k. The likely uncertainties for unconstrained walking paths are $\epsilon_p > \epsilon_r > \epsilon_k$. In part, this is due to the PIR array and radar systems capturing the velocity component along one axis only (i.e., aligned with the PIR array or directly towards or away from the radar). If the sensors are placed in a hallway that constrains the walking path, the uncertainties for the PIR array and radar will be different. It

TABLE I. Physical Sensors

Category	Sensor
Motion sensing	Room sensing Spot sensing (e.g., shower, frig) PIR array
	Magnetic door sensors
	Location tracking (Ubisense)
	Single-camera Multi-camera Kinect depth camera
	Radar Ultrasound Acoustic sensing
	Wearable accelerometers Smartphone mobile device
Bed and chair sensing	Binary mat Load cells under bed/chair Pneumatic transducer Hydraulic transducer Radar on ceiling Ultrasound on ceiling Microphone Accelerometer on the wrist
Medication compliance	Med box lid sensing Mems caps on pill bottles Vision to capture med use
Vital signs	Weight scale Blood pressure Pulse oxygen Glucometer Peak flow meter
Computer use	Interactive cognitive games Key strokes/mouse usage statistics
Other sensing	Statistics on phone usage Audio phone signal (emotions) Stove temperature Water sensing Electric power/signal sensing

TABLE II. Health and Wellbeing

Category	Clinical Use
Early detection and prevention of illnesses	Depression Memory loss Gait dysfunction Infections Sleep disturbances Cancer Malnutrition
Maintaining function	Physical activity Memory Low Anxiety/Stress Social network Fall risk Medication adherence
Managing chronic conditions	Heart disease Hypertension Vascular insufficiency Parkinson's disease Sleep apnea Diabetes Arthritis Prostatic hypertrophy Dementia

is important to understand the measurement uncertainties when using the sensor data for embedded health assessment. Depending on the uncertainty value, a logged history of walking speed might indicate a real trend of the monitored individual as a result of a health change. Or it could be a natural fluctuation due to the sensing modality.

V. Discussion

The proposed approach represents the first step to building a flexible and powerful framework for harmonizing, combining and fusing diverse data sources. The problem of harmonizing data is becoming increasingly important with the availability of big data and with the need to analyze them. In fact, data harmonization is one of the central issues challenging the emerging data science fields. The novel aspect in the sensor data representation is the need for relatively precise temporal synchrony and spatial registration. The conceptual sensor space will enable both. It is also important to note that the CS representation is just a first necessary step in building a framework for real time assessment, inference and intervention.

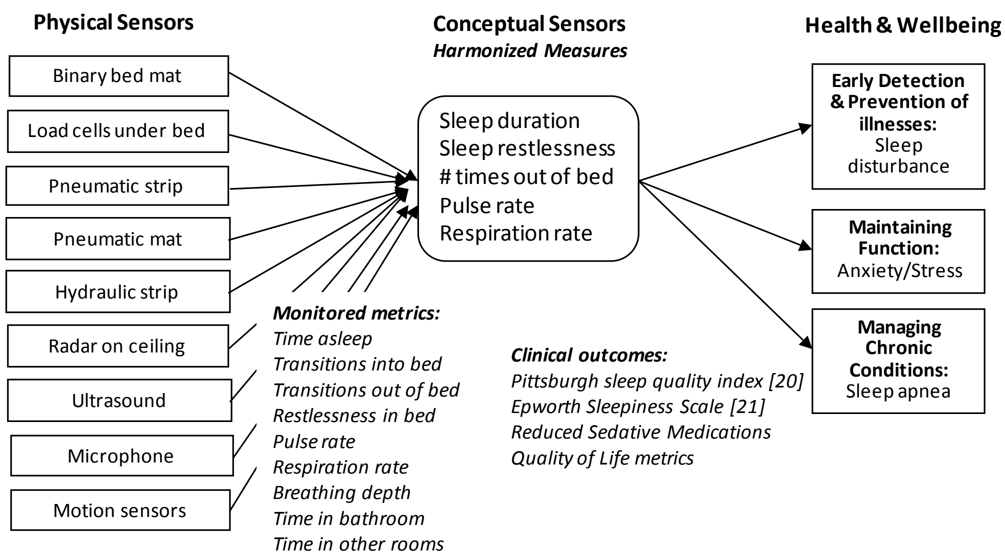

Fig. 2. A *Conceptual Sensor* example used for sleep quality

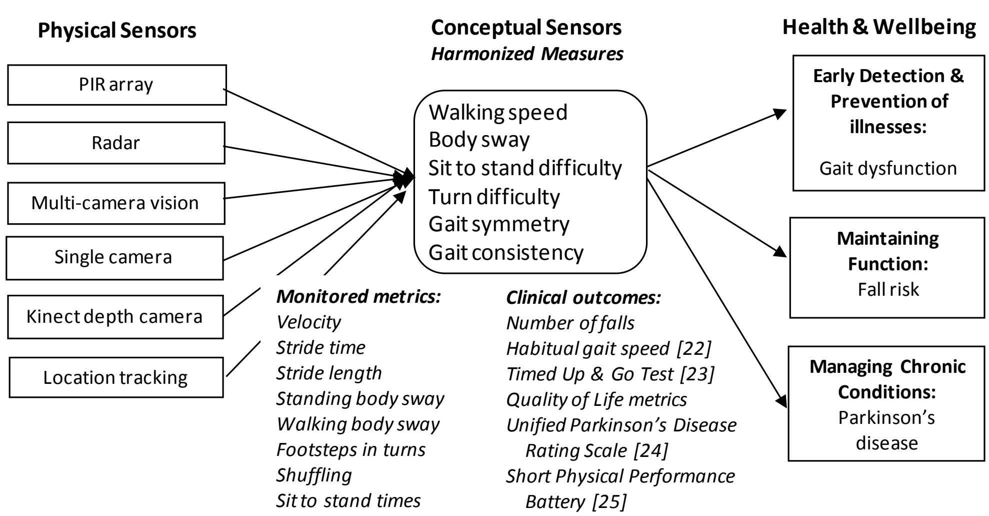

Fig. 3. A Conceptual Sensor example used for ambulatory physical function

REFERENCES

[1] K. McCabe (2008, October 1). *IEEE Approves Seven New Health Informatics Standard*. http://standards.ieee.org/announcements/IEEE_NewHealthStandards.html.

[2] IEEE 11073™ Standard Committee. (2008, December 19). IEEE 11073 Part 10471™: Device specialization - Independent living activity hub. *IEEE 11073 Part 10471™: Device specialization - Independent living activity hub* . New York, New York: IEEE.

[3] ASTM Subcommittee E31.25. (2010). *ASTM E2369 - 05e1*. Retrieved 2010, from ASTM International: http://www.astm.org/Standards/E2369.htm

[4] M.J. Rantz, M. Skubic, R.J. Koopman, G. Alexander, L. Phillips, K.I. Musterman, J.R. Back, M.A. Aud, C. Galambos, R.D. Guevara, and S.J. Miller, "Automated Technology to Speed Recognition of Signs of Illness in Older Adults," *Journal of Gerontological Nursing*, 2012, vol. 38, no. 4, pp.18-23.

[5] N. Krishnan and D. Cook. "Activity recognition on streaming sensor data," *Pervasive and Mobile Computing*, 2014, vol. 10, pp. 138-154.

[6] H. Jimison, M. Pavel, and T. Le, "Home-based cognitive monitoring using embedded measures of verbal fluency in a computer word game," *Proc IEEE Eng Med Biol Soc,* vol. 2008, pp. 3312-5, 2008.

[7] C. Galambos, M. Skubic, S. Wang, and M. Rantz, "Management of dementia and depression utilizing in-home passive sensor data," *Gerontechnology*, 2013, vol. 11, no. 3, pp. 475-468.

[8] G. Rescio, A. Leone, and P. Siciliano, "Supervised Machine Learning Scheme for Wearable Accelerometer-Based Fall Detector," *Springer Sensors and Microsystems, Lecture Notes in Electrical Engineering*, Volume 268, 2014, pp. 295-299.

[9] D. Anderson, R.H. Luke, J. Keller, M. Skubic, M. Rantz and M. Aud, "Linguistic Summarization of Video for Fall Detection Using Voxel Person and Fuzzy Logic," *Computer Vision and Image Understanding*, 2008, vol. 113, pp. 80-89.

[10] E.E. Stone and M. Skubic, "Fall Detection in Homes of Older Adults Using the Microsoft Kinect," in press, *IEEE Journal of Biomedical and Health Informatics.*

[11] L. Liu, M. Popescu, M. Skubic, M. Rantz, T. Yardibi & P. Cuddihy, "Automatic Fall Detection Based on Doppler Radar Motion," *Proc, Intl Conf on Pervasive Computing Technologies for Healthcare*, Dublin, Ireland, May 23-26, 2011, pp 222-225.

[12] Y. Li, K.C. Ho and M. Popescu, "A Microphone Array System for Automatic Fall Detection," *IEEE Transactions on Biomedical Engineering*, 2012, vol. 59, no. 2, pp. 1291-1301.

[13] T. Henderson and E. Shilcrat, "Logical sensor systems," *Journal of Robotics Systems*, 1984, vol. 1, no. 2, pp. 169-193.

[14] M. P. Lawton, "Environment and other determinants of well-being in older people," *The Gerontologist*, 1983, vol. 23, pp. 349–357.

[15] T.C. Havens, J.C. Bezdek, J.M. Keller and M. Popescu, "Clustering in ordered dissimilarity data," *Int. J. Intelligent Systems*, 2009, vol. 24, no. 5, pp. 504-528.

[16] D. Anderson, J. Bezdek, M. Popescu and J. Keller, "Comparing fuzzy, probabilistic, and possibilistic partitions," *IEEE Transactions on Fuzzy Systems*, 2010, vol. 18, no. 5, pp. 906-918.

[17] J. Kaye, N. Mattek, H. Dodge, T. Buracchio, D. Austin, S. Hagler, M. Pavel, and T. Hayes, "One walk a year to 1000 within a year: Continous in-home unobtrusive gait assessment of older adults," *Gait and Posture*, 2012, vol. 35, no. 2, pp. 197-202.

[18] F. Wang, M. Skubic, M. Rantz, T. Yardibi, and P. Cuddihy, "Quantitative Gait Measurement with Pulse-Doppler Radar for Passive In-Home Gait Assessment," in review, *IEEE Transactions on Biomedical Engineering*.

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

[20] D.J. Buysse, C.F. Reynolds, T.H. Monk, S.R. Berman, and D.J. Kupfer, "The Pittsburgh Sleep Quality Index: A New Instrument for Psychiatric Practice and Research," *Psychiatry Research*, 1989, vol. 28, no. 2, pp. 193-213.

[21] M.W. Johns, "Sensitivity and Specificity of the Multiple Sleep Latency Test (MSLT), the Maintenance of Wakefulness Test and the Epworth Sleepiness Scale: Failure of the MSLT as a Gold Standard," *Journal of Sleep Research*, 2000, vol. 9, no. 1, pp. 5-11.

[22] R.W. Bohannon, "Comfortable and maximum walking speed of adults aged 20-79 years: Reference values and determinants," *Age and Ageing*, 1997, vol. 26, pp. 15-19.

[23] D. Podsiadlo, and S. Richardson, "The Timed Up & Go: A test of basic functional mobility for frail elderly persons," *Journal of the American Geriatrics Society*, 1991, vol. 39, pp. 142-148.

[24] C. Ramaker, J. Marinus, A.M. Stiggelbout, B.J. van Hilten, "Systematic evaluation of rating scales for impairment and disability in Parkinson's disease," *Movement Disorders*, 2002, vol. 17, no. 5, pp. 867–876.

[25] J.M. Guralnik, E.M. Simonsick, L. Ferrucci, R.J. Glynn, L.F. Berkman, D. Blazer, D., et al., "A short physical performance battery assessing lower extremity function: Association with self-reported disability and prediction of mortality and nursing home admission," *Journal of Gerontology*, 1994, vol. 49, pp. M85-M94.