An Eldercare Electronic Health Record System for Predictive Health Assessment

Mihail Popescu, George Chronis, Rohan Ohol, Marjorie Skubic, Marilyn Rantz

Abstract—**Many older adults in the US prefer to live independently for as long as they are able, despite the onset of conditions such as frailty and dementia. Sensor networks have emerged in the last decade, together with telehealth and internet based electronic health records (EHR), as a possible solution to older adult health monitoring. Many commercial solutions for EHRs, telehealth monitoring and sensor networks are available but, as far as we know, no integrated system exists. In this paper we present an integrated eldercare EHR system (IEEHR) that merges health data with sensor and telehealth (vital signs) measurements. The benefit of an EEHR system is three fold: provides physicians a wider gamut of tools for chronic disease management, reduces nursing workload and allows the development of health context aware algorithms for predictive health assessment. In this paper we present the integrated EEHR system we are developing at TigerPlace, an assisted living community in Columbia, Missouri. Several examples of possible applications are also presented.**

Index Terms—**Eldercare, Electronic Health Records, Sensor Networks, Telemedicine, Predictive Health Assessment**

I. Introduction

MANY older adults in the US prefer to live independently for as long as they are able, despite the onset of conditions such as frailty and dementia. Elderly patients are particularly at-risk for late assessment of physical or cognitive changes due to many factors: their impression that such changes are simply a normal part of aging; their reluctance to admit to a problem; their fear of being institutionalized; and even the failure of physicians to fully assess their function due to the belief that no intervention is possible [1].Solutions are needed to enable independent living while enhancing safety and peace of mind for the elder adults' families [3], [2].

Sensor networks, telehealth and internet based EHRs have emerged in the last decade as possible solutions to older adult health monitoring. Elderly monitoring using sensor networks has traditionally evolved from home security solutions and it mostly involves motion detectors, such as GE QuietCare, and/or video cameras, such as the solutions offered by Acadian Monitoring Services, Inc., (http://www.americaonwatchnetwork.com.)

Telehealth solutions are mostly used by nursing organizations to monitor selected patients with chronic diseases such as diabetes, PTSD and depression. Many suppliers of telehealth equipment (blood pressure, blood oxygen, blood sugar and weight monitoring together with the data transmission hub) are available such as Honeywell's (http://www.honeywell.com) Genesis suite, Bayes' (http://bayer.com) Viterion products and Tunstall's (http://www.tunstall.co.uk) ADLife system.

Commercial nursing electronic medical records (EMR) systems are offered by many companies such as: SigmaCare (http://www.sigmacare.com), HealthMEDX (http://www.healthmedx.com), Mobile Physician Technologies (http://www.par3emr.com) and AOD Software (http://www.aodsoftware.com). In spite of the crowded EMR software market only 1% of the US skilled nursing facilities have adopted an EMR as opposed to 18% of the US hospitals [4].

Several academic monitoring environments such as MIT's PlaceLab [5], Georgia Tech's Aware House [6] and Honeywell's Independent Lifestyle Assistant [7] have been demonstrated. Many other monitoring solutions for older adults such as the ones found in [8], [9], [10] and [1], employed a variety of sensors and algorithms to detect activity patterns and assess medication compliance, fall risk or dementia.

In this paper we present an integrated eldercare EHR system (IEEHR) that merges health data with sensors and telehealth (vital signs) measurements. The benefit of an IEEHR system is three fold: provides physicians more tools for chronic disease management, reduces nursing workload and allows the development of health context aware algorithms for predictive health assessment. As far as we know, none of the existing monitoring solutions has considered the health context of the resident in developing monitoring algorithms. For example, a hospitalization may change the normal behavior, while a medication change may affect sleep patterns or fall risk. The IEEHR we develop at an aging in place facility, TigerPlace, situated in Columbia, Missouri [12], allows us to introduce health context aware monitoring algorithms able to detect and predict early signs of illness and functional decline based on telehealth and sensor data.

The structure of the paper is as follows: in section II we present the architecture of our IEEHR, in section III we describe in more details the EHR component, in section IV

M.P. is with the Health Management and Informatics Department, University of Missouri, Columbia, MO 65211, USA (corresponding author, phone: 573-882-1266; fax: 573-882-6158; e-mail: popescum@missouri.edu).

G.C. is with CyberSense, LLC, USA, email: george@cybersense.us

R.O. is with the Carolinas Medical Center, Charlotte, NC.

M.S. is with the Electrical and Computer Engineering Department, University of Missouri, Columbia, email: sckubicm@missouri.edu

M.R. is with the University of Missouri Sinclair School of Nursing.

we briefly describe several examples of health context aware algorithms we develop in TigerPlace and in section V we give the conclusions.

II. IEEHR System Architecture

TigerPlace [11] [12] is an independent living facility for seniors designed and developed as a result of collaboration between Sinclair School of Nursing, University of Missouri and Americare Systems Inc. of Sikeston, Missouri. The primary goal of TigerPlace is to help the residents not only manage their illnesses but also stay as healthy and independent as possible. We have been monitoring TigerPlace volunteer residents with in-home sensor networks since fall, 2005.

An overview of the architecture of the proposed IEEHR system is shown in Fig. 1.

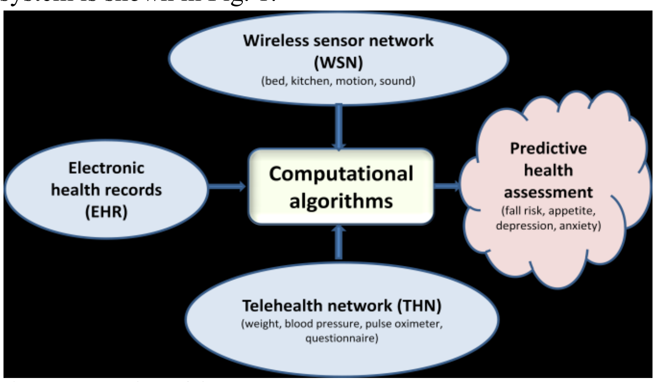

Figure 1. Overview of the IEEHR system

The proposed IEEHR system interconnects the existing wireless sensor network (WSN) at TigerPlace with a telehealth network (THN) and a personalized electronic health record (EHR).

The *WSN* captures external behavioral information about the monitored person and contains various wireless, non-wearable, sensors such as motion, cabinet, stove and bed sensors. The decision to employ only non-wearable sensors in TigerPlace was based on multiple focus groups with TigerPlace residents performed early in our project [13,14]. As part of the WSN, each resident included in the sensor network study has a data logger in his/her apartment that collects data from various wireless sensors. The data logger date-time stamps the data, and sends it to a database on a secure server via a wired network connection. Thirty-seven sensor networks (without video) have been installed in TigerPlace apartments to date; the video component of the network will be installed early next year. The sensor network consists of several types of sensors mounted in different places throughout the residents' apartments, including motion sensors, bed sensors, and stove temperature sensors. The bed sensor consists of a pneumatic strip [9] placed on top of the mattress, that captures qualitative pulse and respiration rates and bed restlessness; we also have a new bed sensor using a hydraulic strip placed under the mattress [15] that captures quantitative pulse and respiration rates. The motion sensors are placed in various places, such as the living room, kitchen, bedroom, bathroom, on the ceiling over the shower, in the laundry closet, in the refrigerator, and in kitchen cabinets and drawers. We are in the final stage of developing vision, sound and radar based sensors that will extend our comprehensive monitoring platform to capture gait and mobility data as well as fall detection. The sensor data are logged in the sensor database which is one of the components of our data storage system. [12].

The *THN* contains in-home networked medical devices, such as a weight scale, blood pressure (BP) meter and pulse oximeter that capture medical data (vital signs) on user demand. The data is currently sent to a remote server and it is periodically downloaded and linked with the personalized electronic health record (EHR) database at TigerPlace. In addition, the telehealth network is designed to capture residents' answers to short health questions that may be used to inform the caregiver or as ground truth for algorithm development. Possible questions from the telehealth questionnaire include the following: "How was your night?"; "Did you fall yesterday"; "How is your appetite today"; and "Did you speak to a nurse yesterday?" The telehealth equipment used at TigerPlace is produced by Tunstall (http://www.tunstall.co.uk/) and consists of a hub model RTX3370, a blood pressure cuff device "A&D Medical UA-767PBT", an oximeter device "Nonin Onyx II" and a weight scale model "A&D Medical UC-321PBT". The vital signs sensors transmit the data wirelessly to the hub using a Bluetooth connection. The wireless glucose meter will be available early next year. The hub records the readings of the sensors and sends them to a remote server.

The *EHR* system captures the following data about a TigerPlace resident: demographics, ICD-9 diagnoses, medications, emergency room visits, hospitalization records, nursing progress notes, nursing visits, assessment forms (SF-12, mood scale, fall assessment, mini mental state exam-MMSE), interim physician orders (IPO), reimbursement forms (HCFA-485), and activities of daily living (ADL). The nursing visit module records information about vital signs and certain assessment questions; health data are entered into the EHR system during the weekly wellness visit or during visits requested by the resident. The progress note module is used by TigerPlace staff to share information about a resident. The ADL module assists the nursing staff to record and assess daily activities of each resident. The EHR system is described in more detail in Section III.

The EHR and THN health data are used for providing contextual information and ground truth for algorithm development. Information about current diagnoses, medication and hospitalizations is factored into the algorithm development process. Our computational approach is based on the assumption that early illness will translate into changes in behavior, such as abnormal sleep or room motion patterns that can be captured by the environmental sensors (e.g., movement or bed activity).

III. TigerPlace EHR Description

The EHR software stretches beyond the sole purpose of storing electronic health records and provides tools targeted to several field professionals as well as residents of long term care facilities. It is a role structured system, which identifies a logged in user based on their function and displays a custom user interface depending on the user's access rights. For example, a nurse would have access to certain forms such as HCFA-485 and assessments, a nurse aide or social worker would have access to visit forms, a Minimum Data Set (MDS) manager would have access to health data as they pertain to the MDS, a physician would be able to log in the system and sign HCFA-485 forms etc.

A system manager role is created that empowers the creation of other users and the definition of their privileges in the system. With proper scalability and expandability considerations our EHR software may be configured for different facilities, adapt to new forms and regulations, meet ever changing HEPA requirements and provide tools for residents and their families that are not typical of EHR systems. For example, a resident may log in the system and access his own health history, visit data and assessments. They may also complete assessment tests online that make use of computer technology, such as audio and video. In addition, the resident's family members may remotely log in to the system and monitor the elder adult's health progress. The system notifies all interested parties once an action takes place and prompts the right individuals for subsequent actions to take place when necessary.

Data is transmitted via a secure encrypted connection to and from the web application interface but it is not stored in the client device. In case a device (such as a laptop or mobile phone) is stolen, compromised or lost, no sensitive data is at risk. Redundant network connections in the facility ensure access to the data and a local mirror of the database is also updated every 24 hours in case of all network connectivity being lost.

The user interface is designed by human interface guidelines specialists to be used without the need of instructions or a user manual by any logged in user (be it a health care professional, a business professional, a resident or a family member). Asynchronous JavaScript and XML (AJAX) programming is extensively used to enhance system response speed and interactivity with the user. Open web development standards are used for compatibility with all desktop and mobile device browsers without the requirement of extensions or royalties.

In the near future we plan on establishing a communication between the EHR, WSN and THN as well as an MDS system to evaluate the system in a real environment. Additional functions such as more enhanced physician information and accounting software integration are continuously being developed.

IV. Examples of Predictive Health Assessment Algorithms

An integrated eldercare EHR system allows the development of predictive health assessment algorithm such as fall risk assessment, high blood pressure detection or mood assessment. These algorithms integrate the values provided by various sensors, telehealth devices and medical conditions to alert the nursing personal when a dangerous level of a certain condition is reached (i.e. elevated fall risk). In the next subsections we present two examples of predictive health assessment algorithms.

A. *Predicting blood pressure using sensor data*

In [16, 17] we used bed and movement sensor data to predict the pulse pressure trend. We conducted a retrospective pilot study on two residents of the TigerPlace aging in place facility, with age over 70 and blood pressure measured between 100 and 300 times during a period of two years. The blood pressure values were manually extracted from nursing visit reports. A robust regression model was used to compute the pulse pressure (see Fig. 2) based on the total number of motion and bed sensors during the night and day time respectively (4 features). The pilot study suggested that pulse pressure trends can be reasonably well estimated (average relative error of less than 10%) using apartment motion and bed sensors.

B. *Predicting good/bad days based on sensor data*

We have used multiple approaches to predict abnormal or "bad" days depending on the data available. In [19, 20] we predicted bad days for TigerPlace residents based on bed and motion sensor data. In that work, due to the strong class imbalance present in the data (few "bad days" labels available), we employed a one-class classifier (OCCs) approach. The main advantage of using a classifier is that we avoid multiple alerts related to the same clinical event when several monitored variables (e.g., bathroom motion, bed motion, etc.) have values out of the normal range [20]. After comparing several OCCs for a pilot dataset, we concluded that this approach is promising if ground truth data is not available. However, if annotated data is available, a two-class classifier approach is preferable [19]. In that case, we hand annotated sensor data for three TigerPlace residents based on the nursing visits. Even for annotated data, there are still methodological challenges due to the uncertainty in terms of time and content of the annotations. For example, if at 10 am, a nurse asks, "How was your night?" and the resident answers "Worse than usual", we would not know when the "unusual" event happened during the previous

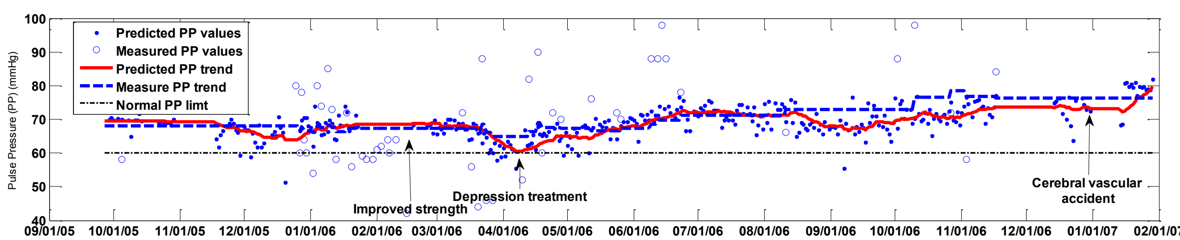

Figure 2. Comparison of the computed vs. measured pulse pressure for a male resident

night or the nature of the event. To address ground truth uncertainty problems, we investigated a multiple instance learning approach (MIL) [19]. In Fig. 4 we show the ROC curves obtained by using a nearest neighbor (NN) classifier with both MIL and OCC frameworks for predicting the quality of the night for a TigerPlace resident. For this case, the MIL-NN classifier was better that the OCC based classifiers (NN and support vector machine-SVM). In [19], we concluded that the MIL based approach was found to be superior to the OCC based approach. In this project we propose to continue to investigate MIL in the context of sensor data that is automatically annotated by our new system that will integrate the sensor network with the electronic health record and a telehealth network. To address the data uncertainties, we will develop a new fuzzy MIL framework that is described in the next section.

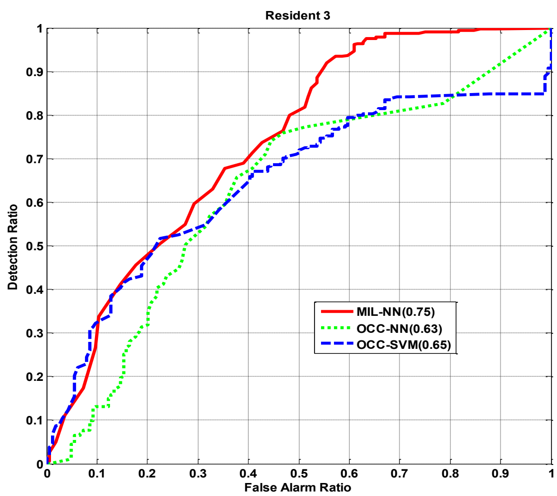

Figure 3. Comparison between MIL and OCC for a TigerPlace resident

V. CONCLUSIONS

Healthcare IT offers potential for better healthcare and independent living as people age. While there are major challenges—such as cost, efficiency, standardization and security—solutions are in sight. Here, we describe an integrated eldercare EHR system allows the development of novel computational approaches to context aware predictive health assessment. This project leverages ongoing work at the University of Missouri (MU) in the use of sensor technology for in-home health assessment. We have deployed sensor networks in the homes of seniors, with a wide range of sensor types and analysis approaches. We are integrating our sensor networks with an EHR and a telehealth network and continue to investigate health context aware computational algorithms for health and wellbeing assessments.

ACKNOWLEDGEMENTS

This work has been supported in part by the following NSF grants: IIS-0428420, HCC-0703692 and CNS-0931607.

REFERENCES

[1] Hayes TL, Pavel M, Kaye JA (2004). An unobtrusive in-home monitoring system for detection of key motor changes preceding cognitive decline. *Proc. of the 26th Annual Intl. Conf. of the IEEE EMBS*, pp. 2480-2483, San Francisco, CA.

[2] Rowan J, Mynatt ED (2005). Digital Family Portrait field trial: support for Aging in Place. Proc. of the SIGCHI Conf. on Human Factors in Computing Systems, pp. 521-530), New York: ACM Press.

[3] Cuddihy P, Weisenberg J, Graichen C and Ganesh M. Algorithm to automatically detect abnormally long periods of inactivity in a home (2007). *Proc. of the 1st ACM SIGMOBILE Intl. Workshop*, pp. 89-94, New York.

[4] Pacicco, S., "The current state of EMRs in Long term care setting", *Nursing Homes*, February 1, 2008.

[5] Intille SS, Larson K, Munguia-Tapia E, Beaudin J, Kaushik P, Nawyn J, et al (2006). Using a live-in laboratory for ubiquitous computing research. Berlin: Proc. of Pervasive;

[6] Kidd CD, Orr RJ, Abowd GD, Atkeson IA, Essa B, MacIntyre B, et al (1999). The Aware Home: A living laboratory for ubiquitous computing research (position paper): Proc. of the 2nd International Workshop on Cooperative Buildings-CoBuild '99.

[7] Haigh KZ, Kiff LM, Ho G (2006). Independent Lifestyle Assistant: Lessons learned. Assistive Technology;18: 87-106.

[8] [Beckwith03] Beckwith R (2003). Designing for ubiquity: The perception of privacy. *Pervasive Computing*; (April-June):40-6.

[9] Mack D, Alwan M, Turner B, Suratt R, Felder R (2006). A passive and portable system for monitoring heart rate and detecting sleep apnea and arousals: Preliminary validation. Arlington VA: Proceedings Transdisciplinary Conference on Distributed Diagnosis and Home Healthcare (D2H2).

[10] Barnes NM, Edwards NH, Rose DAD, Garner P (1998). Lifestyle monitoring: Technology for supported independence. *Computing and Control Engineering Journal*; (August):169-74.

[11] Rantz MJ, Dorman-Marek K, M. Aud, Tyrer HW, Skubic M, Demiris G, et al. (2005) A technology and nursing collaboration to help older adults age in place. Nursing Outlook; 53:40-5.

[12] Skubic M, Alexander G, Popescu M, Rantz M & Keller J (2009). A Smart Home Application to Eldercare: Current Status and Lessons Learned, Technology and Health Care, 17 (3), pp. 183-201.

[13] Demiris G, Rantz MJ, Aud MA, Marek KD, Tyrer HW, Skubic M, and Hussam AA (2004). Older adults' attitudes towards and perceptions of 'smart home' technologies: a pilot study. *Medical Informatics*, 29, 87-94.

[14] Demiris G, Hensel BK, Skubic M, and Rantz MJ (2008). Senior residents' perceived need of and preferences for "smart home" sensor technologies," *International Journal of Technology Assessment in Health Care*, vol. 24, no. 1, pp. 120-4.

[15] Heise D & Skubic M (2010). Monitoring pulse and respiration with a non-invasive hydraulic bed sensor. Proc.,32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Buenos Aires, Argentina.

[16] Popescu M, Florea E, Krampe J, Skubic M, Rantz M (2008). Prediction of the pulse pressure trend in elderly using in-home monitoring sensors: a pilot study", Proc of IDAMAP-08, Washington DC, pp. 29-33.

[17] Popescu M, Florea E (2008). Linking Clinical Events in Elderly to In-home Monitoring Sensor Data: A Brief Review and a Pilot Study on Predicting Pulse Pressure. Journal of Computing Science and Engineering, Vol. 2, No. 1, pp. 180-199.

[18] Popescu M, Mahnot A (2009). Acoustic Fall Detection Using One-Class Classifiers. Proc. 31th Int. Conf. of the IEEE EMBS, Minneapolis, MN, Sept 2-6, 2009, pp. 3505-3508.

[19] Popescu M, Mahnot A (2010). Early illness recognition in older adults using in-home monitoring sensors and multiple instance learning. Proc of IDAMAP-10, Washington DC, pp. 21-25.

[20] Alexander GL, Rantz M, Skubic M, Koopman RJ, Phillips LJ, Guevara RD & Miller SJ (under review). Evolution of an early illness warning system to monitor frail elders in independent living.