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Passive In-Home Health and Wellness Monitoring: Overview, Value and Examples

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Abstract—**Modern sensor and communication technology, coupled with advances in data analysis and artificial intelligence techniques, is causing a paradigm shift in remote management and monitoring of chronic disease. In-home monitoring technology brings the added benefit of measuring individualized health status and reporting it to the care provider and caregivers alike, allowing timely and targeted preventive interventions, even in home and community based settings. This paper presents a paradigm for geriatric care based on monitoring older adults passively in their own living settings through placing sensors in their living environments or the objects they use. Activity and physiological data can be analyzed, archived and mined to detect indicators of early disease onset or changes in health conditions at various levels. Examples of monitoring systems are discussed and results from field evaluation pilot studies are summarized. The approach has shown great promise for a significant value proposition to all the stakeholders involved in caring for older adults. The paradigm would allow care providers to extend their services into the communities they serve.**

I. Introduction

THE majority of the world's increasing older adult population requires some degree of formal and/or informal care due to loss of function as a result of failing health. In the US, for example, nearly three quarters of older adults suffer from one or more chronic diseases according to the Centers for Disease Control (CDC). The cost and burden of caring for older adults is steadily increasing [1]. Changes in the Medicare system in the US led to a shift in the responsibility for care from institutions to the community (individuals and families). Informal caregivers have experienced increased physical burdens and emotional strains as a result of this shift in long-term care responsibilities. Furthermore, healthcare providers are faced with a shrinking professional work force at the same time [2]. On the other hand, the proportion of the world's population of individuals over the age of 60 is expected to double by 2030 to 20%. In the US, the number of older adults is expected to grow to 108 million over the next 15 years, which represents 45% of the adult population. Older adults currently account for 60% of the overall healthcare spending in the US. Furthermore, 92% of these older adults live alone in their own apartments, homes, independent living facilities, or assisted living facilities, including about 50% of those 75 and older [3]. Such statistics clearly demonstrate an urgent need for innovative telehealth/ telecare tools that enable older adults to live independently. These tools also help to maximize caregivers' efficacy by providing timely health information that enables them to deliver more effective care. This demographic change, and its potential economic impact on industrialized nations has prompted active research in AI-based systems for automated functional and health status monitoring and assistance. A comprehensive review of research on the potential of exploiting automation technologies to better equip caregivers is provided in [4]. In the meantime, the use of modern sensor and communication technology, coupled with advances in data analysis and artificial intelligence techniques, is already causing a paradigm shift in remote management and monitoring of chronic disease. This technology brings the added benefit of measuring individualized health status and reporting it to the care provider and caregivers alike, allowing timely and targeted preventive interventions, even in home and community based settings [5].

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Health monitoring in the home environment can be accomplished by a) ambulatory monitors that utilize wearable sensors and devices to record physiological signals (reviewed in [6]); b) sensors embedded in the home environment and furnishings to unobtrusively collect behavioral and physiological data; or c) a combination of the two [6]. Passive monitoring has the inherent benefit of obviating the problems associated with incorrect use and subject non-compliance, thus we will focus our attention on passive, non-constraining health monitoring.

Throughout the reminder of the paper, a model for geriatric care that is enabled by in-home monitoring and ambient intelligence technologies will be presented. Over the past few years, the Medical Automation Research Center (MARC) at the University of Virginia has been developing, validating, refining and evaluating passive monitoring technologies that fit the technology-enabled care paradigm. The paper will also briefly describe example systems developed at MARC that conform with the presented care delivery model.

II. Model for Geriatric Care Enabled By Technology

The use of information technologies in the care environment has a perceived value on the levels of administration, integration of services, care quality, and professionalism [7]. It can be argued that a new paradigm for geriatric care can emerge with more integrative technologies, for example, if the activities and selected physiological parameters of an older adult are monitored in his/her own living setting. This can be accomplished by placing sensors in the older adult's living environment or on the objects they use in the environment; the environment is the place the older adult calls home and it may be the older adult's home in the community, or their residence in a continued retirement community, independent living apartment, assisted living unit, etc. Safety, activity, physiological, health and socialization data can be analyzed, archived and mined to detect indicators of early disease onset, or changes in health conditions.

Data analysis results, at various levels, could be made available to all stakeholders in the care process, including the older adults themselves, their professional caregivers and eldercare provider, informal caregivers, and primary health care provider. The results would then be integrated into an electronic or personal health record accessible to authorized caregivers in the older adult's network whenever they need them.

The monitored individual can use the results in personal health maintenance (e.g., diet, exercise). Informal caregivers will get objective assessment of their loved one's ability to remain independent, along with peace of mind. It is believed that this reassurance will eliminate the interrogation, questioning, and role reversal between the older adult and their adult children and would increase the social content in their communications. This is expected to improve the quality of life for both parties, and reduce unnecessary early institutionalization of older adults driven by the anxiety of their children.

When the older adult needs assistance with some of their Activities of Daily Living (ADLs) or Instrumental Activities of Daily Living (IADLs), professional caregivers accessing the reports will have an objective assessment of their actual needs and will be able to determine the appropriate care services. This allows them to coordinate, dispatch and track the delivery of care and services to the monitored older adults whether through home care agencies (e.g., meals on wheels, bathing) if they live in the community, or through on-site direct care workers if they live in a care facility.

Primary health care providers can have a more comprehensive, longitudinal evaluation of the monitored older adult's health than the snap shot assessment obtained during an annual physical examination. This may enable them to better detect early onset of disease and prescribe appropriate interventions, including preventive treatments, and monitor the efficacy of these interventions objectively over time.

Access to the results of the same objective data at various levels by the different stakeholders is expected to improve the communication dynamics between the different stakeholders (e.g., the eldercare provider and the adult child when deciding on the most appropriate care package for the older adult).

This paradigm exploits the technical capabilities of embedded sensing, ambient intelligence, interoperability and interconnectivity between different devices in the home. as well as other information and communication technologies, to automate the continuous assessment, documentation, and communication processes. This facilitates and enables the coordination and delivery of high-touch care through a network of professional and informal caregivers that are able to deliver the care when needed. This paradigm is expected to result in prolonged and enhanced independence of seniors, delay in their transition to nursing facilities and lead to a reduction in the overall cost of care.

III. Examples of Passive Monitoring Systems

A. *Activity Monitoring System*

MARC's activity monitoring system is comprised of several off-the-shelf wireless motion sensors and a threshold temperature sensor above the kitchen stove. All sensors transmit data wirelessly to a PC-based appliance. This dedicated computer appliance collects all the sensors' data and periodically dials into a secure remote data server. The in-home data collection appliance also runs routines to check possible emergent conditions. A web-based inference application performs pre-programmed data analysis routines on the transferred data and then displays the results inferred from the sensors in an intuitive format.

The system was tested for 18 months in a community home that served as a "living laboratory". In preliminary studies, the activity data of a normal healthy middle-aged participant was logged and analyzed using several data analysis techniques including clustering, mixture models [8] and a rule-based approach, where spatial-temporal relationships among sensor events are exploited to infer the occurrence of activities with a high degree of confidence. The basic set of rules and algorithms were developed using knowledge acquisition principles to generate generic rules that would be applicable to almost anyone. This starting point could be used as a template that could be later refined and customized to a specific resident or client while maintaining computational efficiency and scalability.

As an example, let us consider meal preparation. Meal preparation would generally entail at least motion in the kitchen and use of cabinets where food, plates and/ or utensils are stored. Depending on the type of meal, it may also involve the use of appliances such as the stove, oven, or microwave.. A rule describing meal preparation activity could be:

IF *the resident was in the kitchen* AND *(resident accessed meals ingredients cabinet* AND *resident accessed plates or utensils cabinet*) OR *resident used an appliance* THEN *a meal was prepared*

Presence in the kitchen can be inferred by motion in the kitchen persisting for a minimum period of time, whereas use of meals ingredients can be indicated by use of a food storage cupboard or the refrigerator. The rule-based approach was adopted for the inference of the activities of interest for its simplicity, computational efficiency, and scalability. Clustering and mixture models as well as the experimentation with the rule-based inferences, allowed limiting the number of sensors used while maintaining an acceptable level of confidence when making inferences. The system and rule-based inference methods were validated against 37 days of the subject's self-report, recorded in real-time using a Personal Digital Assistant (PDA) based electronic diary developed specifically for the validation study. The validation results of the activity inference rules were reported in [9]. The knowledge-engineered rules were compared to rules automatically generated by supervised learning using random forest. Results have shown an acceptable validity of knowledge-engineered rules compared to automatically generated rules [10].

B. Passive Sleep Monitor

MARC's Non-Invasive Analysis of Physiological Signals (NAPS) system uses ballistocardiography (BCG) to detect minute forces generated during cardiac contraction and relaxation, and can also detect body movement from respiratory effort and postural changes. Preliminary data [11] have shown strong correlations between the heart rate passively measured using the NAPS system and conventional clinical techniques such as pulse oximetry. The NAPS system relies on a highly sensitive pressure transducer pneumatically connected to a resilient force-coupling pad installed on top of the mattress of any standard bed, on which the subject lies in order to acquire the data. Multiple pads can be used to acquire data from different parts of the body. Algorithms were developed [12] to provide automatic scoring of the instantaneous heart rate and respiration data recorded by the NAPS system. Additional data analysis techniques were developed to identify sleep stages (Wake, non-REM and REM Sleep) as well as apneas and arousals [13].

The ability of the NAPS system to measure heart rate, as compared to electrocardiogram (ECG), and its apnea and arousal detection capabilities, as compared to conventional polysomnography, were investigated. The NAPS average heart rate was highly correlated with the ECG average heart rate ($r = 0.972$, $p < 0.0001$). The NAPS System failed to produce an average heart rate for an epoch 10.6% of the time, with the majority of those being due to movement artifacts. Apneas and arousal events detected with the NAPS system were compared to those detected with polysomnography using 2-way contingency comparisons, without discriminating between central and obstructive apneas (all hypopneas were included as well). Overall, the NAPS system achieved a sensitivity of 89.2% and specificity of 94.6% in the detection of apneas with a kappa correlation coefficient of 82.8%. The kappa correlation was chosen since the technician scored polysomnography data is also subject to errors. Moreover, the NAPS system attained a sensitivity of 77.3% and a specificity of 96.2% in the detection of arousals with a kappa of 73.0% [12].

C. Passive Fall Detector

MARC's floor vibration based fall detector uses a special piezoelectric sensor, coupled to the floor surface by means of mass and spring. This sensor is combined with preprocessing electronics to evaluate the vibrations of the floor. The size of the detector assembly is comparable to a small coffee-can and it can be placed directly on the floor, typically one per large room. The detector continuously monitors the floor for vibrations that are produced by the common activities of the resident like walking, sitting down, tapping etc. Based on the experiments conducted, it was noted that there were significant differences in the patterns of vibrations induced on the floor by different activities.

A significant difference in the vibration pattern generated by a dropped object as compared to a falling anthropomorphic dummy or person was found. This difference was effectively used to detect the falls with a higher degree of sensitivity and fewer false positives. The device detects an impact as a possible fall only when the vibration pattern (frequency, amplitude, duration, etc.) obtained from the floor over a small period of time matches the pattern induced when a person falls on the floor. The detector can then report the possible fall alert to the responder through an appropriate communications portal, such as the telephone line, to send a message to a radio pager or cellular phone.

The integrated fall detector was tested using anthropomorphic dummies. The performance of the detector for non-fall events was tested by dropping objects weighing 5 pounds and 15 pounds at various distances covering the entire range of detection, up to 20 ft. The tests, both for the dummy and objects, were repeated on different flooring treatments (carpet with and without foam padding) to evaluate the effect of floor treatments on the performance of the fall detector.

The fall detection range for the sensor was found to be 20 ft. in the case of mezzanine concrete floor covered with linoleum and 15 ft. on concrete slab floor. The fall detector attained 100% detection rate of falling dummies and 0% detection rate of dropped objects having a weight of 15 lb. as close as 2 ft. away from the sensor (100% sensitivity and 100% specificity from a total of 70 dummy falls and 53 object drops). The performance was not significantly affected by different floor treatments including linoleum, carpet, and foam padding [14].

The same sensor technology has shown promising ability to detect step-induced floor vibrations and provide various basic gait parameters including step count, cadence, and step duration. Additionally, it has shown some ability to distinguish between normal, limping and shuffling gait modes. The gait monitor may be augmented with additional sensors to estimate the distance of walking subjects and evaluate average walking velocity. This would enable the calculation of additional gait characteristics such as average step length and average stride length. These parameters can be used to detect various gait anomalies and evaluate fall risk.

D. *Instrumented Walker for Gait and Balance Monitoring*

Under the passive assessment paradigm, the author developed, with collaborators, a method that allows the passive assessment of basic walker-assisted gait characteristics, including heel strikes and toe-off events, as well as stride time, double support and right & left single support phases. This was accomplished using only force-moment measurements from the walker's handles. The passively derived gait characteristics of 22 subjects were validated against motion capture gait analysis. The force-moment based heel initial contact detection algorithm has produced a high level of concordance with heel initial contacts detected by a human inspecting the heel marker data sets of the Vicon® video motion capture system. The algorithm has demonstrated 97% sensitivity and 98% specificity with a narrow 95% Confidence Interval of ±1% during all experiments, which included 5 navigational scenarios. Temporal error in detecting the instances of heel initial contacts were within 5.27±3.66% of the overall stride time obtained from video motion capture when the subjects walked in a straight line, whereas the toe-off instance estimation were within 5.18±2.75% of the gait cycle. The errors in determining the duration of stride time, single support, and double support were within 5.86±2.49%, 5.24±2.29%, and 4.34±2.13% of the gait cycle respectively. The estimated stride time, using the method presented here, correlated well with stride time computations based on visual inspection of motion capture data, having a Pearson correlation coefficient of 0.86 for straight line segments. However, absolute errors were too high to estimate the single and double support phases with acceptable accuracy [15].

Similarly, resolving the forces and moments applied on the walker's frame to its center of gravity allows computing a stability measure that accounts for the vertical load distribution on the walker and the effect of angular loads. Specifically, moments about the right and left side axes of the walker's can be computed continuously. The value of the stability margin indicates the stability of the walker platform under the user's influence. In general, if the walker is unstable, the human user is very likely to also be unstable [16]. A potential application for the instrumented walker and the gait and stability assessment methods is performing longitudinal basic gait and stability assessment outside of the conventional gait labs.

IV. Conclusion

The passive in-home health status monitoring technologies is already bringing about a new technology-enabled paradigm for geriatric care that would allow care providers to extend their services into their larger community. The approach warrants field evaluations to further prove its imapcts on health outcomes, effectiveness, efficiencies of caregivers and care providers, and cost-effectivesness in different care settings through large scale demsonstartion projects.

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