Generating Sensor Data Summaries to Communicate Change in Elder's Health Status

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Keywords

Sensors, health care technology, assisted living facilities, activities of daily living

Summary

Background: Sensor systems detect critical health changes of frail residents in the community. However, sensor systems alone may not allow users to identify data trends fast enough. Linguistic summaries of sensor data describing elder activity in their apartment provide a useful solution so clinicians can respond quicker.

Objectives: This paper describes two case studies of independent elders living with sensors in their assisted living apartment. Residents experienced declining health status and activity level over a period of approximately 24 months. Linguistic summaries were assessed iteratively by engineers and nurses working with the sensor system.

Methods: We created summaries of activity data collected from sensors located in resident apartments during a period of health status change. Engineers distilled information from heterogeneous data sources including bedroom motion and bed restlessness sensors during the summarization process. Engineers used fuzzy measures to compare two different periods of nighttime activity. Using iterative approaches a registered nurse worked with the team to develop algorithms and short phrases that appropriately capture and describe changes in activity levels.

Results: Total activity levels captured by sensors were graphed for two elderly residents experiencing health problems over a period of months. In the first case study (resident 3004), an elderly resident had knee surgery and onset of backspasms postoperatively. Graphed dissimilar measures show changes from baseline when backspasms occur. In the second case study (resident 3003), there were increased periods of bed restlessness before and after a resident had a major surgical procedure. During these periods, graphs of dissimilarity measures indicate that there were changes from usual baseline periods of restlessness postoperatively indicating the health problems were persisting. Nurse care coordination notes indicate these episodes were related to poor pain control.

Conclusions: Summaries of activity change are useful for care coordinators to detect resident health status for community dwelling residents.

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1. Background

Demand for independent living is expected to increase as baby-boomers age in the next 25 years [1]. One factor preventing independent living is undetected health status change leading to greater functional decline and increasing dependence. Our research to date has focused on integrating non-wearable sensor systems for monitoring health status of elderly residents in independent living (TigerPlace) [2, 3]. Sensor system users (family, resident's, nurse's, physician's) have provided valuable input for early designs of computer screens and potential uses [4]. The novelty of our sensor system is that it is being tested in an actual assisted living facility with live residents who have been living with sensors, some over 8 years, with nurse care coordinators who can assess the level of health status change based on sensor data. Additionally, care coordinators can facilitate earlier intervention by communicating with physicians about changes in health status detected by sensors to implement a new care plan. However, current interfaces being used contain densely populated multi-colored figures that illustrate data trends deeply embedded across multiple screens. These figures are useful but can require significant cognitive workload and time for users to interpret. Furthermore, alerts generated by the sensor system only provide information about when the alert occurred (i.e. daytime or nighttime alert), resident identification, and a link to data where the health status change occurred. Additionally, there are links with each alert message to progress notes and visit notes when alerts are generated.

Users have suggested further enhancements in the design of the sensor system including linguistic summaries of sensor data that provide a narrative view of health status changes detected by sensors [5]. This narrative view will improve current views that include colorful histograms and density maps illustrating resident activity levels in their apartment. The summaries can be sent electronically through the early illness alert system which has been previously tested [6]. We believe the summaries will facilitate earlier detection, faster clinical decision making when residents are declining, resulting in earlier intervention, and better health outcomes for elders. Testing these assumptions about the use of linguistic summaries will be the work of future studies by our research team.

1.1 Theoretical Underpinnings of Linguistic Summarization

The key to linguistic summarization is fuzzy set theory and fuzzy logic [7]. Fuzzy set theory is a mathematical way to model the natural unavoidable uncertainty present in monitoring the well-being of humans [8]. Fuzzy logic provides a way to deduce new conclusions from premises in light of uncertainty [9]. For example, we can describe days worth of sensor data (typically, several megabytes of information) using linguistic concepts such as *moderate* depression or *sharp recent decline* in daily activity. This requires some mathematical modeling for detecting differences and/or similarity of total activity levels detected by sensors from baseline measures over time. Fuzzy logic is the best way to represent the context dependent uncertainty of the medical concepts being conveyed.

1.2 Sensor Systems to Monitor Health Status Change

TigerPlace provides our research team with a unique interdisciplinary opportunity to evaluate sensor systems in collaboration with the University of Missouri, Sinclair School of Nursing, Electrical and Computer Engineering, Health Informatics, Health Professions, Social Work, and Medicine. These collaborations resulted in research projects which have improved quality of life and care of seniors who want to age in place.

TigerPlace is staffed by a Registered Nurse (RN) Care Coordinator. The care coordinator provides an array of services such as medication management, assistance with activities of daily living, care coordination of health conditions with residents' physicians, and Medicare home health care is arranged when needed. The care coordinator also provides ongoing monitoring and response to the current early illness alert system that incorporate alert notifications about declining health status [10]. The special setting of TigerPlace, with the unique capability of the RN Care Coordinator, helps position our methods to not only be successful, but to be pioneering in its results to help elders maximize their independence.

A variety of passive sensors are available for detecting motion, location, and activity in resident apartments in TigerPlace. Passive sensors are embedded in a person's environment and are not worn. The sensor system works through passive infrared motion detection, which uses X10 technology. A data monitor collects motion and bed sensor information, time-date stamps each sensor firing, generates a file and transmits it to a central server as a de-identified data file. Sensor events are recorded onto an activity logger for residents who have sensor systems. Embedded within this sensor system is a behavioral reasoning module used to build a clinical decision support system which initiates alerts to providers or family members about important events. Sensors provide information about functional activity, operationalized as where a resident spends most of their time in the apartment, such as in the living room or bedroom. Functional activity levels throughout the day and night are captured by sensors mounted on walls, above doorways, and in common pathways used in the resident's apartments. Sensors also monitor physiological data including restlessness and vital signs. Restlessness and vital signs, including heart and breathing rate, are monitored with a flat electronic device developed by engineers that fits under the resident's mattress [11]. More detail about the sensor system is discussed elsewhere [6]. Every data element can be visualized thorough a web-based interface to determine total activity patterns, mark adverse health events, and establish criteria for alert generation.

1.3 Data Sources

In preliminary work, we crafted a sensor system capable of providing effective, accurate and clinically relevant health alerts generated from the sensor data [5]. The health alerts were sent via an electronic health record to care coordinators who used the information to prospectively detect signs of early illness and to plan appropriate interventions for residents [12]. While placing a variety of sensors in each resident's living space yields a wealth of information, a major issue is rooted in how to expedite analysis of massive amounts of clinically relevant data collected by care coordinators and sensors using current visualization methods. Further integration of these data sources provides opportunities for further development of message prototypes, such as linguistic summarizations of the data collected by sensors about health status.

In previous work, our research team introduced a method to linguistically summarize human activity from video used to monitor the well-being of elders and to detect adverse advents such as falls [13]. Example summaries from previous research include, *"There is a high confidence that Sally has fallen and is on the ground for a moderate amount of time in the bedroom"*, or *"There is a moderate confidence that Sally is lying on the couch in the living room for a long time with little motion this morning"*. The goal of this method is to produce rich, succinct human readable explanations of activity in a natural format for the purpose of information reduction and complexity management. The goal of the current exploratory work is to use similar methods using sensor data collected retrospectively from two residents to create linguistic summaries of their total activity during nighttime, including bedroom motion and bed restlessness activity.

Objective

Our objective is to use a test bed of sensor data collected by sensors to detect early health status changes using two cases where nighttime activity was known to have changed as a result of illness.

Method

3.1 Study Design

We incorporate a case study methodology to explore the use of linguistic summaries. Case studies are used to analyze and understand issues that are important to the history, development, and circumstances of an individual, family, group, institution, community, or other social units [14]. Our interdisciplinary team of engineers and nurses used an iterative process of reviewing sensor data in-

cluding total activity detected by sensors for bed restlessness and bedroom motion, recommending clinically relevant text to include in summaries of sensor data, and adjusting algorithms to capture sensor data while simultaneously displaying summarized information. For this study we evaluated sensor data associated with only bedroom motion and bed restlessness because they seem to be particularly sensitive to health status changes detected in preliminary work [12, 15]. All subjects have consented with approved Institutional Review Board procedures.

3.2 Participants

Two residents with documented health status changes were purposively selected for these case studies to explore the use of linguistic summaries to detect health status change.

Case Study 1

For our first case study (resident 3004), we selected an elderly individual who had been living with sensors for 8 years and who was known to be experiencing health status changes at the same time. This participant was an 89 year old male. This gentleman has past history of hyperlipidemia, muscle spasms, back pain, joint pain, and joint replacement. Surgeries include a Total Right Knee Replacement and back surgery for injury from car accident. This participant was independent in all activities of daily living at the time of the case study. He still drives, volunteers, and works out daily.

We reviewed bedroom motion and bed restlessness sensor data for six months on this elderly resident (► Figure 1a). During this period, resident 3004's health status was stable until the resident underwent an elective knee replacement (► Figure 1a). Following the knee replacement, resident 3004 was temporarily relocated to a skilled nursing facility for rehabilitation and was eventually brought back to TigerPlace. Resident 3004 started outpatient physical therapy rehabilitation and continued this for several weeks upon his return to TigerPlace. During his exercise regimen it was noted by the healthcare team that the resident wasn't effectively extending his right leg when working out. To address this issue the resident obtained a new orthotic shoe and his leg extension improved. Later, the resident began having complaints of backspasms and another order was obtained for more physical therapy. Reported symptoms were relieved following therapy.

Case Study 2.

Our second case study (resident 3003) included an 80 year old male with a past history of carotid artery stenosis and hypertension. He also has a history of episodic syncope and bradycardia with a pacemaker placement. While being monitored by sensors, the resident underwent a Coronary Artery Bypass Grafting (CABG) procedure while living at TigerPlace, a year later he suffered from a stroke (► Figure 1b), and subsequently died. Prior to his death, he was living independently with some personal care assistance at TigerPlace.

We reviewed bedroom motion and bed restlessness sensor data during this period of decline (► Figure 1b). During this period, the residents bedroom motion and bed restlessness appear to be fairly stable except for the few weeks just after his CABG surgery. Care coordinators confirmed, during this period, that the resident was having pain control issues. The resident eventually went to live with family for assistance until he felt better, when he moved back to his apartment. This activity corresponds to Figure 1b labeled as the period of time resident not in room. During the time that he lived with family after his CABG he had no bed data being reported, but there was some bedroom motion from regular visitors in his apartment, during the day.

3.3 Measures

The sensors at Tigerplace provide a continuous data collection system that monitors total activity levels of residents around the clock. Therefore, large amounts of data are collected that need to be analyzed by healthcare providers. However, analyzing data using plotted graphs, like those illustrated in ► Figure 1, makes it difficult for healthcare providers to detect subtle changes from normal baseline measurements. So, better interfaces using novel automated detection systems, better data visualization, and customized outputs are needed to facilitate faster decision making. To facilitate this, engineers implemented a time series analysis method based on linguistic summaries that are

short natural language sentences, which can be displayed electronically in order to capture the essence of the data. Fuzzy sets were employed to model the imprecision of human language [16, 17].

We further analyzed linguistic summaries by estimating the similarity of measures between two nights. For this we used fuzzy logic to detect differences between two sets of summaries. For example, in ►Figure 1a, sensors indicate activity data for resident 3004, who had knee replacement surgery. After returning home from his surgery the sensors appear to detect some change in bedroom motion and bed restlessness data compared to earlier periods of baseline activity. Using fuzzy measurements engineers can measure and assess similarities or differences between these nights to discover health status changes detected by sensors and can provide a set of human readable linguistic summaries that inform the healthcare provider about health status change.

Using an iterative process, engineers and nurses familiar with the sensors and care coordination processes tested possible linguistic summaries and quantifiers to describe changes in bed restlessness and bedroom motion activity [18]. Initial linguistic summaries were realized using an identified attribute, such as bedrestlessness, and a quantifier. Quantifiers used for this case study to be included in linguistic summary prototypes were *all*, *almost all*, *most*, *many*, and *a few*. Also, three linguistic values were incorporated into the summaries including *low*, *medium*, and *high* to further define the range of activity change detected by sensors. Validity of linguistic summaries incorporating the select attributes and quantifiers were assessed along with the similarity or dissimilarity of two measures at different time intervals[19]. Quantifiers were iteratively reviewed by clinicians to assess granularity of sensor data broken into different time intervals. For this analysis, clinicians suggested 15 minute time intervals to maximize data granularity associated with linguistic summaries.

Prototype summaries describing resident 3004's typical nighttime activity were created from 2 weeks of data, when the baseline appeared consistent and no health changes were documented by care coordinators. Prototype linguistic summaries for this case study were compared to nighttime bedroom motion and bed restlessness sensor data from 9:00PM to 7:00AM during four periods beginning with night time activity starting at Baseline Day 1 and Baseline Day 2; then, nighttime activity starting 6 months after the initial baseline assessments (►Table 1). These time frames were selected because they corresponded to before and after resident 3004 had surgery.

Prototype summaries describing resident 3003's typical nighttime pattern were produced from linguistic summaries over a period when no health status changes were occurring according to nurse care coordinators. We compared baseline prototype summaries with nighttime activity data with dates before and after resident 3003's stroke event. Final summaries are illustrated in ►Table 1.

We can compare those nights by providing a similarity value computed as the similarity between sets of summaries [16]. Based on the similarity between the baseline value and analyzed nighttime value the nights were cut into three distinct categories: similar nights, somewhat similar nights, and different nights. These categorical differences were plotted and are illustrated on ►Figure 2a and ►Figure 2b for resident 3004 and resident 3003, respectively.

4. Results

4.1 Total Activity

Total activity for bed restlessness and bedroom motion detected by sensors for resident 3004 (►Figure 1a) is graphed and provides an illustration of the baseline bed restlessness and bedroom motion activity. An assessment of this raw data indicates the resident's baseline activity level for bedroom motion and restlessness appears consistent with little change. There is one area when the resident appears to have no activity because he was out of the apartment for significant period time. Upon return to his apartment, just before surgery, his restlessness level appears to be slightly elevated from earlier months, but bedroom motion appears about the same. Following surgery, the resident's bedroom motion appears to sharply increase immediately after returning home from skilled nursing, while bed restlessness declines. Later, each of these appears to return to baseline.

Total activity for bed restlessness and bedroom motion detected by sensors for resident 3003 (►Figure 1b) is graphed and provides an illustration of the baseline bedroom and bed restlessness activity. An assessment of this raw data indicates that baseline measures for bed restlessness is fairly

stable (approximately 50–100 sensor firings) except for the period just after the resident returned home from having the CABG procedure, when the firings dramatically increased. Bedroom motion had consistently less than 50 sensor firings during this period.

4.2 Similarity Measures

By graphing the similarity measures for resident 3004 in ► Figure 2a we can determine more accurately that a few points of dissimilar and many more points of somewhat dissimilar measures are detected between baseline and postoperative activity levels. The periodicity of the somewhat dissimilar measures appears to increase with the onset of the backspasms experienced by this resident postoperatively. Clearly there is a difference in the similar measures at baseline compared to the measures postoperatively, indicating that this resident is still experiencing some difficulties in his health status and has not returned to baseline.

Graphs of similarity measures for Resident 3003 in ► Figure 2b also illustrate distinct dissimilar nighttime activity compared to baseline activity immediately postop after the CABG surgery. This increased activity corresponds to care coordination documents indicating the resident had poor pain control, subsequently he was moved to a family residence for assistance. Upon returning home, after respite with family, the resident's activity levels appeared to return to more similar patterns to baseline; until, a few weeks prior to the stroke and just after the stroke event when his restlessness and bedroom motion pattern was somewhat similar to his usual pattern.

4.3 Linguistic Summaries

Prototype summaries for Resident 3004 were derived from these measures for 4 nights and are illustrated in ► Table 1. Prior to surgery, at baseline, when measures were mostly similar and somewhat similar (► Figure 2a) most 15 minute intervals of data were low bedroom motion, low bed restlessness, or a combination of both. This set of values indicates that when the resident was in bed there was no bedroom motion and he was not restless in bed on this particular night. The second baseline day indicates that there is a higher level of bedroom motion activity accompanied by increased bed restlessness. There appear to be no high levels of bedroom motion or high bed restlessness activity that occur during this stable period.

Linguistic summaries of sensor data for Resident 3004 detected following surgery describe that almost all 15 minute intervals of medium bedroom motion also had low bed restlessness. Compared to the first two baseline days, the level of motion appears to have increased at some intervals from low to medium, with similar amounts of bed restlessness. This summary may correspond to differences seen in sensor data postoperatively in ► Figure 1a. This finding could be related to the episodes of pain from the back spasms. Additionally, this activity summary would make intuitive sense since the resident would be experiencing increased bedroom motion he would not be in bed as much, therefore periods of restlessness would also decline.

Linguistic summaries for Resident 3003 are provided in ► Table 1. Although, the similarity measure indicates that more nighttime activity patterns are somewhat different than usual, just prior to stroke and just after, this difference is difficult to determine in the linguistic summaries alone. However, we can see in ► Figure 2b that nights before stroke are only somewhat similar, which may indicate a health status change could be taking place. Changes in summaries noted include a reduction from many episodes of medium bedroom motion and bed restlessness to only low levels of bedroom motion and bed restlessness. Perhaps these changes in health status are so subtle at this point that it is difficult to determine changing status without triangulating these different methodologies. We know, from our preliminary work, that health status change is detectable up to 2 weeks in advance before any real symptoms emerge, but these differences may be subtle, difficult to assess, and hard to recognize with the naked eye without use of these types of sensing instruments and decision support systems [12].

5. Discussion

Linguistic summarizations provide a means of sifting data sources to help clinicians identify vital information that could mean better outcomes for patients. These methods facilitate quicker access to critical information which previously might have gone unnoticed until something bad happened to a resident. Using the power of sensor technology we are developing better ways to monitor, evaluate and provide services for elderly people who want to maintain independent lives in a setting of their own choice. However, there are still important issues we have to address to make the use of linguistic summaries safe and reliable to use. For example, we need to operationalize critical variables like bed restlessness and bedroom motion and create appropriate algorithms for measuring similarities and differences of these types of activity levels to be used in clinical decision support systems.

The use of sensor systems to compile data about a resident's activity levels has created the opportunity to collect and identify new information. Bed restlessness, for example, is a common term used by nurses to describe a patient's level of agitation. In this study bed restlessness is operationalized as the amount of patient movement in bed over a certain period of time. In our sensor system, increasing amount of movement detected above a certain standard deviation from baseline over a period of a few seconds would generate a bed restlessness alert that would be sent to a care coordinator [2, 5]. Restlessness in bed is a difficult concept to quantify because of the variability caused by sleeping habits or underlying health conditions. Use of sensor systems may help us to understand the phenomenon of restlessness better than we previously have, so that treatments and interventions can be adjusted accordingly. Future work will incorporate sensors that will be more sensitive to other vital signs such as breathing and heart rate at the same time we are monitoring restlessness which will help make our assumptions more reliable and valid [11].

The novel use of big data sets created by sensor systems in independent living provide new ways of detecting changes in health status and activity. However, algorithms that support the use of these clinical decision support systems are in their infancy. In these early stages of development interdisciplinary teams of researchers will be required to work together to arrive at solutions that will be safe and reliable for clinicians to use. Healthcare professionals such as nurses and physicians are needed to ensure that the parameters such as language used and alert algorithms for clinical decision support have appropriate fit with clinical criteria. Engineers and informatics professionals are required to make sure the infrastructure of the information system improves classification, accessibility, and retrievability of data. Additionally, the inclusion of iterative, user centered approaches incorporating the views of residents living with sensors and their families will continue to be an important part of our research. We have found that residents feel safer living with our sensors, but they have some particular concerns about who is viewing their data and how it is being used [3, 20].

6. Limitations

There are limitations to our work. It is difficult to identify conclusively, from only two case studies, if linguistic summaries generated from total activity levels used to monitor health status change effectively contribute to earlier notification about health status changes. We do know, based on preliminary work, that our current sensor system, without linguistic summaries, does provide benefits to RN care coordinators who are monitoring residents for health status change [12, 21, 22]. It is our assumption that enhancing the current system with linguistic summaries that provide automated interpretation of underlying data will help with decision making when a change is detected from baseline total activity measures. A limitation of our current summaries in this study is that we only incorporate data from two sensor types including bedroom motion and bed restlessness. Integrating summaries from other sensor sources, such as, total activity in living room, bathroom, etc. would provide a more holistic review of actual resident activity levels.

Further research is needed incorporating rigorous prospective, iterative, user centered design methods to determine if linguistic summaries make intuitive sense to clinicians in the context of resident health status change. Future research will require more interdisciplinary work by our team of engineers and nurses working collaboratively to create and test summaries.

7. Conclusion

Sensor systems in assisted living facilities help clinicians recognize change in activity level and health status earlier. Incorporating linguistic summaries of sensor data should help nurses identify and communicate activity and health status change even earlier. Summaries created from appropriate algorithms and designed from clinically appropriate evidence based criteria will be required to make these algorithms safe and reliable. Interdisciplinary partnerships between healthcare professionals and engineers are necessary to create systems that are usable.

Clinical Relevance Statement

Sensor systems that collect data about elder activity levels are novel systems that can help clinicians to remotely monitor people who want to live independently in the community but who are frail. Sensor systems capture a large amount of data which makes it difficult for clinicians to assess quickly if health changes are occurring. Providing linguistic summaries of the health changes detected by the clinical decision support system to clinicians, that are meaningful, could help pinpoint events that could lead to earlier treatment and fewer adverse events, such as hospitalizations and falls.

Conflicts of Interest

The authors declare no conflict of interest with this study.

Protection of Human Subjects

All activities were approved by the University of Missouri Institutional Review Board.

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Fig. 1 Case study 1: Resident 3004 (a) and Case study 2: Resident 3003 (b) bedroom motion and bed restlessness data from sensors

Fig. 2 Category assignment for summaries from each night as compared with the prototype set of summaries. Case study 1 3004 (a), Case study 2 3003 (b)

Table 1 Linguistic Summaries of Restlessness and Bed Motion of Night Time Sensor Data for Two Cases

Date and Time Interval	Linguistic Summaries Derived from Sensor Data
Case Study 1: Resident 3004	
Baseline Day 1 21:00–07:00	• Most 15-minute intervals are low restlessness. • Most 15-minute intervals are low restlessness and low bedroom motion. • Most 15-minute intervals are low bedroom motion.
Baseline Day 2 21:00–07:00	• Most 15-minute intervals are low restlessness. • Most 15-minute intervals are low bedroom motion. • Many 15-minute intervals are low restlessness. • Many 15-minute intervals are low restlessness and low bedroom motion. • Many 15-minute intervals are low bedroom motion. • Many 15-minute intervals of medium bedroom motion and medium restlessness. • A few 15-minute intervals are medium restlessness.
Baseline Day 1 + 6 months 21:00–07:00	• Almost all 15-minute intervals of medium bedroom motion are low restlessness. • Most 15-minute intervals are low restlessness. • Most 15-minute intervals are low bedroom motion. • Many 15-minute intervals are low restlessness and low bedroom motion. • Many 15-minute intervals are low bedroom motion. • A few 15-minute intervals are medium bedroom motion.
Baseline Day 2 + 6 months 21:00–07:00	• Almost all 15-minute intervals of low bedroom motion are low restlessness. • Most 15-minute intervals are low restlessness. • Most 15-minute intervals are low restlessness and low bedroom motion. • Most 15-minute intervals are low bedroom motion.
Case Study 2: Resident 3003	
Baseline 21:00–07:00	• Many 15-minute intervals have low restlessness • Most 15-minute intervals of medium bedroom motion have medium restlessness • Most 15-minute intervals of low bedroom motion have low restlessness • Many 15-minute intervals have low restlessness and low bedroom motion • Almost all 15-minute intervals of low restlessness have low bedroom motion • Most 15-minute intervals have low bedroom motion • A few 15-minute intervals have medium restlessness
Baseline + 6 months 21:00–07:00	• Almost all 15-minute intervals of low restlessness have low bedroom motion. • Most 15-minute intervals have low restlessness. • Most 15-minute intervals have low restlessness and low bedroom motion. • Most 15-minute intervals have low bedroom motion.
Baseline + 7 months 21:00–07:00	• Almost all 15-minute intervals of low restlessness have low bedroom motion. • Almost all 15-minute intervals of low bedroom motion have low restlessness. • Most 15-minute intervals have low restlessness. • Most 15-minute intervals have low restlessness and low bedroom motion. • Most 15-minute intervals have low bedroom motion.

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