A Rule-Based Approach to the Analysis of Elders' Activity Data: Detection of Health and Possible Emergency Conditions

Siddharth Dalal*, Majd Alwan*, Reza Seifrafi†, Steve Kell*, Donald Brown†

*Medical Automation Research Center, †Department of Systems Engineering
University of Virginia
PO Box 800403
Charlottesville, VA 22908.
{dalal | alwan | swk3f | rs8fd | brown @virginia.edu}

Abstract

In this paper, we present a rule-based approach to the inference of elders' activity in two primary application areas: detecting Independent Activities of Daily Living (IADLs) for the detection of anomalies in activity data patterns consistent with arising health issues over a period of time, and the detection of possible emergency conditions passively and unobtrusively. We discuss our efforts using classification techniques leading to the rule-based inference approach, and compare results between the two approaches. The results have shown the viability and validity of knowledge-engineered rules, which outperformed automatically generated rules using random forest supervised learning; the κ correlation coefficient between the classification results of the random forest model and the PDA record was **0.79**, with **85% sensitivity** and **93% specificity**, compared to **κ=0.84**, with **91% sensitivity** and **100% specificity** for the knowledge engineered rule aimed at the detection of main meal preparation. The paper also presents experimental field trial results of the rule-based approach demonstrating the utility of the method and future directions for our research.

Introduction

The majority of our increasing elder adult population requires some degree of formal and/or informal care due to loss of function as a result of failing health. According to the Centers for Disease Control (CDC), nearly three quarters of elder adults suffer from one or more chronic diseases, examples include arthritis, hypertension and diabetes, to name a few. The cost and burden of caring for elder adults is steadily increasing [1]. Changes in the Medicare system led to a shift in the responsibility for care from institutions (e.g. nursing homes, etc.) to the community (individuals and families). Meanwhile, the role of informal caregivers in providing care to the elder adult population has greatly increased over the past two decades. Consequently, informal caregivers have come to be viewed as an unpaid extension of professional caregivers; providing most of the care to elder adults requiring long-term care. In fact, national databases derived from independent sources have provided unequivocal evidence that family and friends are the sole care providers for about three quarters of all community-dwelling elder adults [2]. Informal caregivers have experienced increased physical burdens and emotional strains as a result of this shift in long-term elder care responsibilities. Furthermore, healthcare providers are faced with a shrinking professional caregiving work force at the same time [3]. 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 elder adults is expected to grow to 108 million over the next 15 years, which represents 45% of the adult population. Elder adults currently account for 60% of the overall healthcare spending in the US. Appropriate management of chronic disease in older adults can reduce the US health care bill by up to 50%. Furthermore, 92% of these elder adults live alone in their own apartments, homes, independent living facilities, or assisted living facilities, including about 50% of those 75 and older. Such statistics clearly demonstrate an urgent need for innovative telehealth/ telecare tools that enable elder adults to live independently and maximize caregivers' efficacy by providing timely health information and delivering more effective care [4]. This change in the demographic, 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 as caregivers is provided in [5]. In the meantime, 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 has the added benefit of measuring individualized health status and reporting it to the primary care provider and caregivers alike; allowing timelier and targeted preventive interventions [6].

Health monitoring in home environments can be accomplished by a) ambulatory monitors that utilize wearable sensors and devices to record physiological signals (reviewed in [7]); b) sensors embedded in the home environment and furnishings to unobtrusively collect behavioral and physiological data; or c) a combination of the two [7]. Passive monitoring has the inherent benefit of obviating the problems associated with incorrect use and subject compliance, thus we will limit the review to passive non-constraining health monitoring systems. Togawa et al was one of the first projects to use passive sensing for everyday activities to monitor subjects both physiologically and behaviorally [8, 9]. One of the pioneering research projects in telehealth was conducted at the University of New South Wales, Australia, aiming to explore whether functional health status amongst the elderly could be accurately determined remotely by continuously monitoring relatively simple parameters that measured the interaction between participants and their environment [10]. The researchers reported a high level of acceptance by both the participants and their primary care providers, since the system was easy to use, effective, and potentially increased the efficiency of chronic disease management. In the United Kingdom, research and clinical trials examined the capabilities of intelligent monitoring systems to identify emergency situations based upon detected deviation from normal activity patterns; of the 61 alerts generated, 46 were classified as false alerts and the other 15 as genuine, although no real emergencies occurred during the study [11]. Acceptance of the technology and its subsequent impact on the participants' quality of life and the caregivers' burdens of care were not evaluated. Currently, research is being conducted at University of Joseph-Fourrier in France [12, 13], focusing on data fusion of multi-sensor information and data mining to generate health alarm conditions. The data analysis methods are tested using simulated physiological data. However, this approach has yet to be validated against clinically accepted standards in a clinical environment. Glascock and Kutzik [14] described a non-intrusive system. In the proof of concept phase, this system was validated in the activities of daily living (ADL) suite of an urban hospital where a video camera and recorder captured the actual activities carried out by participants. An in-home testing phase was sequentially conducted in 1998 in several homes, with the longest monitoring data collected representing 13 consecutive days [14]. However, these results were not validated and the impact of monitoring on caregivers or care-recipients was not assessed.

The Medical Automation Research Center (MARC), at the University of Virginia, has been engaged in developing an automated in-home health status monitoring system in the past few years. In order to develop the sensor suite and refine the activity inference algorithms, 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 [15] 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 latter approach was adopted for the inference of the activities of interest for its simplicity, computational efficiency, and scalability. Clustering and mixture models were useful in only identifying clusters representing activities but did not readily allow the automatic labeling of these clusters, i.e. assigning an activity name to the clusters. Moreover, both methods were computationally expensive, requiring significant learning, and thus may not scale easily. Nonetheless, these methods, together with the experimentation with the rule-based inferences, allowed us to limit the number of sensors used while maintaining an acceptable level of confidence in our 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, reported in [16], are summarized in the result section. In one of our recent studies, 22 monitoring system prototypes were deployed in an assisted living facility [17] to assess the utility of the system to caregivers in coordinating everyday care tasks, as well as the impact the monitoring had on the monitored care recipients. Each monitoring system was comprised of a suite of non-invasive sensors to monitor ambulation, overall activity levels, and use of bathroom, shower, and stove, as well as time in / out of bed, pulse while in bed, and restlessness in bed [18]. A follow-on pilot study, focusing on assessing the diagnostic utility of the system and its impact on the cost of care in assisted-living, is currently underway. In two other pilot current studies, we have recently deployed 37 systems in independent living apartments (25 systems), and homes in the community (16 systems) where the activity data are being reported to home health nurses. The latter two pilots are aimed at assessing the impact of the technology-enabled interventions on the quality of life of monitored individuals and their informal caregivers, informal caregiver burdens, and the efficiencies of professional caregiver.

In this paper, we will present details of our patent pending rule-based activity inferences engine and alert algorithms, using a minimum set of sensors, and show the validity of its inferences, as well as results from the field.

System Description

The data collection systems consist of several off-the-shelf wireless motion sensors, which use the X10 wireless protocol, a patent pending bed monitor consisting of a flexible pad pneumatically connected to sensor system [18] that passively measures breathing, pulse, and restlessness in bed, and a threshold temperature sensor above the kitchen range. All sensors transmit data wirelessly to a PC-based appliance in the subject's assisted-living unit or home. This dedicated computer appliance in the home collects all the sensor generated data and periodically dials into a secure remote data server, located in the MARC Robotics Lab, to write new data into the remote database.

The in-home data collection appliance also runs the routines to check possible emergency conditions. A web-based inference application performs pre-programmed data analysis routines on the transferred data and then displays the inference and analysis results.

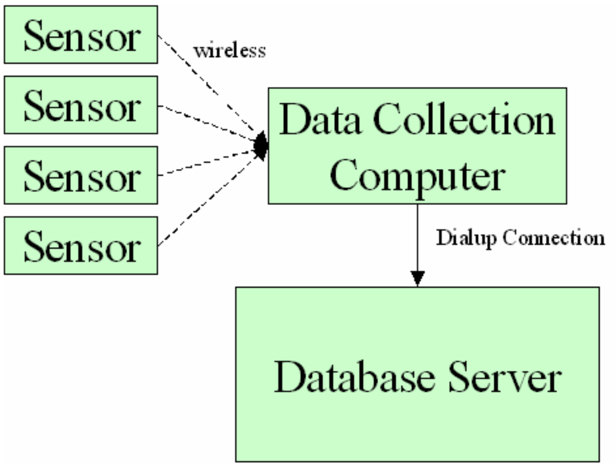


Figure 1. Monitoring System Architecture

ADLs Inference Rules

Correlating the patterns that we found using our efforts described in the introduction with the activities of daily living such as bathing, bathroom visits and meal preparation led us to develop computationally efficient activity inference rules that significantly reduced the computations required for the inferences compared to classification. These rules are associations of groups of specific sensor firings targeted to specific activities of interest, such as Activities of Daily Living (ADLs), which constitute a clinically accepted method to assess an older adult's ability to remain independent. For the purpose of this paper, it is assumed that the resident is living alone at home. If not, another set of rules would be required to determine whether the subject is alone or not before the activity inference rules are invoked. We apply the rules to the raw data to obtain activity information. The inference rules have the generic form:

IF *A* AND/ OR *B* THEN *C*

As an example consider meal preparation. Meal preparation would 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 involve the use of appliances, e.g. stove, oven, or microwave oven. A rule for meal preparation is:

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 indicated 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 etc.

For another example, consider a rule to infer bathroom use. The rule for detecting a bathroom visit is simple:

IF *the resident is in the bathroom* (indicated by motion in the bathroom persisting for a minimum period of time) THEN *a bathroom visit occurred*

However, with additional sensors, such as a sensor mat near the sink, we can distinguish between bathroom visits for different purposes. With the sink mat sensor in place we can more accurately determine bathroom visits for the express purpose of toileting.

The rule in this case would be:

IF *the resident is in the bathroom* (motion in the bathroom persisting for a minimum period of time) AND *the resident is* NOT *on the sink mat* (none to very few firings from the sink mat) THEN *a bathroom visit occurred*

We measure 'persistent motion' in an area by the number of successive firings in that area with a maximum time gap between successive firings. So in our first case without the sink mat, we define a bathroom use event based on at least *n* successive firings of the bathroom sensor with the gap between successive sensor firing not more than two minutes, without the subject leaving the room/ area. We chose the two minute interval because of limitations on the way the X10 sensor functions. The value for *n* for bathroom visits was chosen to be 5. However, this number varies for each individual activity, based on our results from clustering or experience from trial and error, since the clustering was done only for a single individual's data.

The algorithm for a bathroom visit would look like:

→ *Get all bathroom sensor firings for period of interest*
→ *Group all firings that happened within two minutes of each other, with no intervening out of the room sensor firing*
→ *All groups that have five or more firings indicate the occurrence of a bathroom visits*
→ *The bathroom visit started at the first firing in the group and lasted approximately up till the timing of the last firing in the group.*

The basic set of rules and algorithms we develop apply knowledge engineering principles to generate generic rules that would be applicable to almost anyone and can be used as a template which could be later refined. Similar sets of

rules can be created for individual activities. Discovering activities using these rules is computationally inexpensive.
Through our successive field pilots we encountered very few individuals whose data produced false inference results. However, it was possible to significantly reduce the false results through minor modifications to the template rules to accommodate these individuals without affecting the other users. Most of the modifications entailed changing the number of sensor firings required to ascertain presence at a location and the minimum time between these successive firings.

Limitations

The rule-based approach cannot be used for the discovery of unknown activities. However, once such activities are known, the rule-based approach can be used to identify repeat occurrences. Often the rule-based approach does not lead to results with 100% certainty. For example if someone opens a cupboard where food is stored and has motion in the kitchen, it does not necessarily mean that they prepared a meal. However, as discussed earlier, this needs to be addressed up front through the instrumentation of an appliance that is key to the activity of interest or by installing an additional sensor to improve the specificity of the rules, and reduce the rate of false positive detection.

Possible Emergency and Alert Inference Rules

The alert rules are similar to the activity inference rules except that they are checked in near real-time in the home. Since we currently use a regular PC for data collection, we had a reasonable amount of computing power to perform some analysis at the client's side. In case of emergency conditions, this has the advantage of quasi real-time because it is no longer necessary to contact our server, dump data and wait for analysis to be performed.

Customizing the Alert Rules

For the Alert Rules, we have made it possible to customize the rules for individual users based on their floor plan and habits.

Results

Validity of the Rule-Based Inference

A inexpensive ADL monitoring system, similar to the one described above with an extended set of kitchen switches (23 sensors in total: 1 stove-top temperature sensor, 15 kitchen cabinet/ drawer switches including one on the microwave oven's door and one on the gas oven's door, and seven motion sensors placed throughout the house), was installed in the community for 37 days to monitor a middle-aged healthy individual living alone. The subject was given a personal digital assistant (PDA), running custom activity diary software, and asked to record activities in real-time. Rule-based activity inference algorithms were refined on data from 17 days, and data from the remaining 20 days were used for validation. The chi-square statistic was computed for 2X2 contingency tables comparing activities detected by the algorithms to user-logged activities. Cohen's kappa (κ) coefficients was computed as a preferred measure of correlation, since it considered that the PDA log does not necessarily represent ground truth perfectly and is subject to errors and omissions. The sensors and detection algorithms did report events not recorded by the occupant on the PDA. Roughly 80% of these occurrences could be attributed to reporting non-compliance, indicated by failure to record sleep or wake time by the occupant or activities consistent with the presence of visitors in the home. The remaining occurrences may also have been due to non-compliance or may have resulted from cabinets being opened for some reason other than meal activity. In the case of showering activity, this may have been due to reliance only on the motion sensor.

After correcting for subject non-compliance in logging activities, the κ correlation between the all meal detection algorithm and the PDA record was **0.84, with 91% sensitivity and 100% specificit**y when only main meals (breakfast, lunch and dinner) were considered. Including coffee and snacks reduces the value to κ=0.67, with 92% sensitivity and 74% specificity. The difference between the two values is largely due to the number of coffee events that were missed. Similarly, the κ correlation between the shower detection algorithm and the PDA record is 0.69, with 67% sensitivity and 100% specificity. The detection algorithms and the sensory data did not miss any main meals or showering activities recorded on the PDA.

Validation results indicated that rule-based algorithms could successfully detect meal preparation and showering activities using simple low-cost detectors and computationally inexpensive algorithms. The sensors and detection algorithms reported events not recorded by the occupant on the PDA, attributed to reporting non-compliance. Overall, the PDA activity journal proved a good compromise between paper diaries, which are more time consuming to keep, and hence may result in higher non-compliance errors, and video recording, which is considered invasive [16].

Knowledge-Engineered Rules vs. the Random Forest Classification

Data from the above mentioned validation study was used to develop a classification model aimed at detecting meal and non-meal activities in the dataset. Although the test and validation days were the same, the non-meal activities were judged by the model differently from the inference rule; consequently, the number of non-meal activity observations in the data sets was different from that used in the rule-based inference validation. The model included all 23 decision variables, 22 of which were binary variables, denoting whether there was a firing from the corresponding motion, cabinet, or appliance sensor in the selected time window. The remaining decision variable was a numeric variable representing the maximum kitchen temperature in the selected time window. The model's response variable was binary, denoting whether the individual was involved in a meal activity during that time window or not.

The supervised learning methodology employed was random forest, which is a tree-based classification technique. In general, binary tree classifiers repeatedly split the observations in the test/ training set, based on rules developed from the values of the decision and response variables, into two descendent subsets, until further partitioning does not improve the level of homogeneity at a given subset, i.e. the impurity of the subset cannot be reduced. Once partitioning stops, the classification tree is complete [20]. To classify the observations in the test set, the model uses the hierarchical decision rule established by the previously developed tree. Although largely consistent with the fundamentals of the binary tree classifiers, the random forest method is unique. While binary tree classifiers generate a single tree, random forest generates multiple trees based on randomly selected subsets of the training set. Furthermore, in random forest, each observation is classified based on the majority vote of all of the randomly generated trees, as opposed to the vote imposed by the single tree in the case of binary tree classifiers [21].

Once the developed random forest was applied to the validation set, the κ correlation coefficient between the classification results of the random forest model and the PDA record of main meals only, after correcting for non-compliance in the PDA record using the same criteria used in the validation study referenced above, was **0.79**, with **85% sensitivity** and **93% specificity,** compared to **κ=0.84,** with **91% sensitivity** and **100% specificity** for the knowledge engineered rule. Subsequently, another random forest model was constructed based on the training set which included all meals, including snacks and coffee. In contrast, when all meal activities were included in the comparison, and after accounting for the non-compliance in the PDA record, the κ correlation coefficient between the resulting random forest model and the PDA record was 0.65, with 89% sensitivity, and 76% specificity, compared to κ=0.67, with 92% sensitivity and 74% specificity for the knowledge-engineered rule. For the all meals case, the variables most significant to model's classification accuracy were Sensor22 (Oven Door switch), Sensor20 (Flatware drawer switch), Sensor23 (Microwave Oven Door switch), Sensor2 (Office Motion Sensor), Sensor13 (Cereal Cabinet switch), Sensor11 (Dishes, Plates, Glasses Cabinet switch), Sensor4 (Bedroom Motion sensor), Sensor24 (Freezer Door switch), and Temp (Stove-top Temperature sensor) listed in the order of their importance; this is illustrated on the left hand side of graph in figure 2. In the case of main meals only, the variables most critical to the classification accuracy of the model are Sensor23 (Microwave Oven Door switch), Sensor20 (Flatware drawer switch), Sensor11 (Dishes, Plates, Glasses Cabinet switch), Sensor14 (Liquor Cabinet switch), Sensor22 (Oven Door switch), Sensor13 (Cereal Cabinet switch), Sensor21 (Spices and Cookware Cabinet switch), Temp (Stove-top Temperature sensor), and Sensor24 (Freezer Door switch) listed in the order of their importance; this is illustrated on the right hand side of the graph in figure 2.

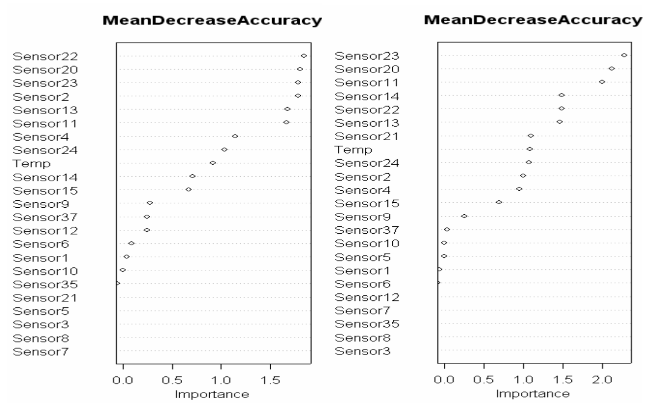


Figure 2. The Importance of the Variables on the Classification Accuracy of Random Forest Meal Detection Model: Left- All Meals, Right- Main Meals Only.

Figure 3 provides an individual binary tree as an example of the binary trees that result from the random forest classifier. In this example if the condition at the node is satisfied the tree decision follows the branch on the left-hand-side, otherwise it follows the right-hand-side. This tree can be interpreted by the following two rules:

IF *the Flatware Drawer was Opened* AND *the Oven Door was Opened* AND *{the Microwave Oven Door was Opened* OR *[(the Microwave Oven Door was* NOT *Opened)* AND *Cereal Cabinet was Opened)]}* THEN *a Meal was Prepared*

IF *Flatware Drawer was* NOT *Opened* AND *the Resident was* NOT *in the Office* AND *the Kitchen Temperature was <u>below</u> 70 degrees* THEN *a Meal was Prepared*

This example clearly points to one of the potential problems of classification: the inability to understand the rationale for the end results, which are very dependent on the training data sets. Hence, generalizations of the end results, are difficult to make. In principle, such generalizations which could facilitate scaling, This study shows that knowledge-engineered rules are viable and produce valid results. In this particular case, knowledge-engineered rules outperformed automatic classification, highlighting the effect and importance of the insight knowledge engineering could have on the results and overall performance of an activity inference engine.

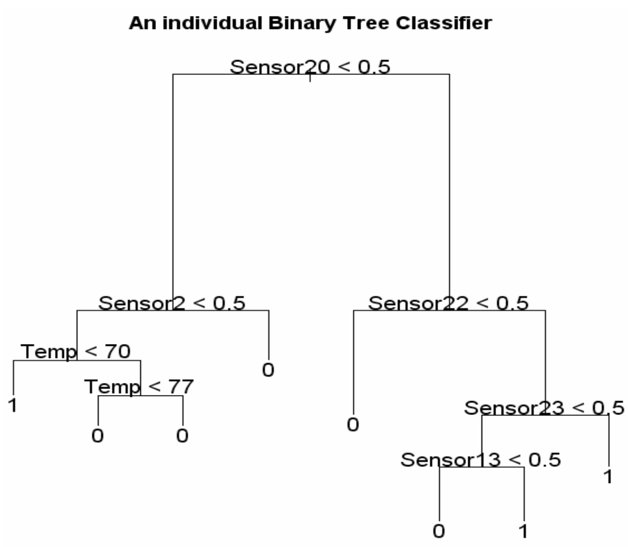


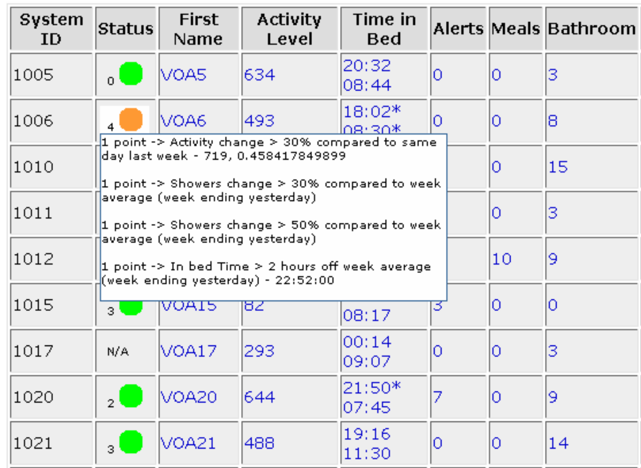
Figure 3. A Sample Binary Tree resulting from the Random Forest Classification Process

Field Results on the Utility of Rule-Based Activity Inference Engine

Using the rule-based approach we have been able to successfully obtain several activities for the research participants including bathroom use, bathing, sleep and wake times and meals. We use these results to obtain patterns of life activities of the participants and evaluate individual well-being based on deviation from that monitored individual's normal weekly routine. Early on we realized that a person's daily activities are naturally dependent on the day of the week, especially in congregate settings, such as assisted-living where residents have regular weekly activity schedules, and thus we compare the individuals' activity to his/ her activity on the same day in the prior week.

Using the results obtained above, on any given day, a caregiver accessing our smarthouse reporting website [19] sees how each individual under monitoring is doing compared to an individualized baseline pattern. We assign points for deviations in activities from the norm. We assign higher values for greater deviation and also apply weighting for certain important events such as large number of bathroom visits between the bed and wake-up times.

Caregivers reviewing the analysis results in the reports, illustrated in figure 4, obtained information that was hitherto unavailable. The information facilitated the detection of several urinary tract infections (UTIs) from frequency of bathroom visits, or increasing pain in memory care residents, from restlessness in bed. By reviewing the summary report of all monitored residents, professional caregivers could not only prioritize their care tasks and schedules, but also know the mood a person would likely be in, based on how well they slept.



System ID	Status	First Name	Activity Level	Time in Bed	Alerts	Meals	Bathroom
1005	0	VOA5	634	20:32 08:44	0	0	3
1006	4	VOA6	493	18:02* 08:30*	0	0	8
1010						0	15
1011						0	3
1012						10	9
1015	3	VOA15	82	08:17	3	0	0
1017	N/A	VOA17	293	00:14 09:07	0	0	3
1020	2	VOA20	644	21:50* 07:45	7	0	9
1021	3	VOA21	488	19:16 11:30	0	0	14

Figure 4. Web-based Summary Report of All Monitored Users

Recent studies have also shown potential cost saving to payers as a result of using the systems data in preventive and early detection of disease conditions. These results will be reported elsewhere.

Field Alert Results

During our first implementation of the Alert System, we aimed to detect and immediately report possible falls, low- and high-pulse (in bed), and possible forgotten stove. The fall alert successfully notified care staff in case of three falls during the study period (Dec. 03 – Jan. 04) [17]. A fourth fall was identified by a low pulse alert – the subject had fallen and was trying to get back into bed. We did, however, have an excessive number of low pulse alerts due to a software bug caused by the Operating System.

We have since resolved this bug and re-implemented the Alert System architecture to accommodate individually customizable rules. We are now testing the new alert system concurrently in three different on-going pilot studies, which have a total of sixty-two participants. In the initial study described above, the generic alerts were successful because all the participants were in similar apartments in an assisted-living facility. In our current studies, the participants are in assisted living, senior independent living, and out in the community. This has led us to discover individuals with unique and sometimes unusual floor plans and/or activity patterns that challenged our existing generic alert rules and generated an unacceptable level of false alerts. We have since modified the alert rules for these users to accommodate individual patterns and residences. We have not reported or missed any defined emergency conditions.

Conclusions

The Rule-based activity inference using knowledge engineered rules is a viable approach to activity inference. Results have shown the acceptable validity of knowledge-engineered rules compared to automatically generated rules, the κ correlation coefficient between the classification results of the random forest model and the PDA record was 0.79, with 85% sensitivity and 93% specificity, compared to κ=0.84, with 91% sensitivity and 100% specificity for the knowledge engineered rules. The results also highlighted the importance of the insight knowledge engineering could have on activity inference results and their validity.

The computationally efficient low-cost system has scaled well to be deployed in the field in over sixty-two homes/ assisted living units without the need for any training periods and has provided caregivers with useful information that facilitated care coordination and delivery of preventive and proactive interventions. These were evidence by the improved quality of life of monitored individuals [17].

Future Directions

As a part of our continuing research in this field, we plan to overcome some of the limitations of the rule-based approach. We can overcome the limitation of uncertainty of an event by assigning a degree of confidence to the result obtained from the algorithm. This degree of confidence can be ascribed based on how many of the criteria set in the rules have been satisfied. Essentially this is enhancing the outcome of the rule based approach using probabilistic approach.

Data → Rules (Data) → Activity with x% certainty

Our results may improve significantly if we incorporate individualized parameters into the ADL inference rules, as we do for the alert rules, instead of attempting to infer the activities of all monitored individuals using the same set of rules, as we currently do.

Data → Rules (Data, Parameters for Individual) → Activity with x% certainty

We also wish to automate some part of the analysis that is currently done by humans. Currently caregivers correlate anomalies in the data to possible disease symptoms by visual inspection of the graphs on the activity reports. We plan to add a higher layer of intelligence on top our rule-based inference results to aid caregivers in identifying possible common geriatric diseases. This additional layer, possibly a neural network, would use the output of the rule-based inference engine and further analyze the deviation from the individual's own baseline to help caregivers obtain early signs of diseases conditions such as UTIs, cognitive decline and others. The analysis done by this layer will be based on current case studies and the intelligence will be enhanced by results from future case studies. As a step towards developing algorithms for detecting onset of Alzheimer's disease, we performed an analysis of the difference in the data between memory care patients and other users in our 22 person study. We discovered statistically significant lower activity levels amongst memory care residents, compared to non-memory care residents. We also discovered that, on average, memory-care residents woke up later than non memory-care counterparts. We will attempt to measure the changes in activity patterns for people who are developing cognitive decline to aid in the early detection and management of cognitive decline.

For the Alert routines, in the future, we hope to have the Alerts learn the user's pattern and customize their rules automatically based on information obtained from past alerts and feedback from the users (either the monitored individual or the caregiver). The application software on the in-home computer will automatically download feedback regarding the veracity of past alerts. If false, it would automatically make adjustments to the alert rules that we currently perform manually. We are advancing towards these goals in our current studies through an NSF funded National Priorities multidisciplinary collaborative project with University of Missouri-Columbia that aims to develop technological interventions for seniors with mobility and cognitive impairments. 12 advanced prototype monitoring systems based on the basic system described here, will integrate additional passive gait monitoring and fall detection capabilities, and be deployed in the TigerPlace assisted-living campus, associated with the University of Missouri-Columbia School of Nursing for further field evaluation.

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of US Patents 5,629,215 and 6,108,685.

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