MEASURES OF EVERYDAY FUNCTIONING IN A SMART ENVIRONMENT: DIRECT OBSERVATION AND DATA MINING TECHNIQUES

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INTRODUCTION

The assessment of everyday functioning has become a topic of interest in aging research. Studies have investigated the importance of assessing and understanding decline in older adults' ability to carry out tasks of daily living and its relation to cognitive functioning[1,2,3]. Some studies have suggested that assessment of everyday functioning may be one of the most ecologically valid ways to measure cognitive decline as it applies to independent functioning in the home[2]. However, "real world" scenarios for assessment of everyday functioning are not commonly used by neuropsychologists, and instead clinicians rely on paper and pencil-based tests, questionnaires, and self-report information to determine impairment in tasks of daily living.

Recent studies have investigated the utility of "smart environments" to assist older adults who are experiencing difficulty with activities of daily living (IADL), such as cooking and cleaning[4,5]. However, smart homes may be able to function as an assessment tool for evaluating difficulties with IADLs, or for determining the need of assistive technology in the home to permit independent living. We evaluated the ability of three types of assessment methods to measure everyday functioning in older adults.

METHOD

Participants were 28 older adults, further separated into two groups: 1) cognitively healthy (n=14; mean age = 72.29 years; mean education = 15.82 years) and 2) mild cognitive impairment (MCI; n=14; mean age = 73.00 years; mean education = 15.57 years) based on a battery of standard neuropsychological tests of memory, attention, speeded processing, and executive abilities, as well as numerous self-report questionnaires, and medical information (criteria for MCI were consistent with Petersen and colleagues[6]). The two groups were matched on age (within 2 years) and education (within 3 years).

<u>Measures of Everyday Functioning</u>

Direct Observation Measure: Participants carried out eight instrumental activities of daily living (IADL) in a smart home testbed on the Washington State University campus. The eight activities included: (1) sweeping the kitchen floor and dusting the dining and living rooms, (2) filling a 7-day medication dispenser with three types of medications, (3) filling out a birthday card along with an appropriate monetary check, and addressing the envelope, (4) operating a DVD player and watching a 5-minute news clip on the television, (5) watering three plants, (6) conversing on the telephone about the 5-minute news clip watched previously, (7) cooking a microwaveable meal of noodle soup, and (8) selecting an outfit appropriate for a job interview.

Direct observation data was collected by two experimenters observing the participant who was carrying out the eight activities. The experimenters coded the participant's actions based on the accuracy of completion, as well as sequence of steps completed. Two additional researchers coded six types of errors (based on the previously explained data collection): 1) critical omission, 2) critical substitution, 3) non-critical omission, 4) non-critical substitution, 5) inefficient action, and 6) irrelevant action. Table 1 provides detailed code assignment information for each error and Table 2 shows the scoring rubric used to derive an overall score for each activity. The overall score for each of the 8 activities was summed to derive the direct observation score.

Laboratory Measure: Participants completed the Everyday Problems Test[7] (EPT), a paper and pencil-based measure of everyday abilities. The EPT requires participants to solve simulated "real world" tasks that involve various ADL domains (e.g., shopping, transportation, meal preparation).

Sensor Data Mining Method: The WSU smart home testbed (CASAS) is a two-story apartment with a living room, dining room, and kitchen on the first floor, and three bedrooms and one bathroom on the second floor. It contains different types of sensors, including 51 motion sensors on the ceiling, door sensors on the refrigerator, microwave door, and on the cabinets, and item sensors on various items such as a medication dispenser. In addition, the apartment contains power sensors and temperature sensors to monitor power usage and the temperature of the rooms. See Figure 1 for the sensor layout and of the apartment.

When a participant performs the eight IADL tasks, the various sensors are triggered. These sensor events are then recorded into a database and do not contain activity specific information. Thus, they are manually annotated later so as to relate sensor events with a specific activity that has been performed at that time.

From the annotated data we extracted various features that represent how well the participant performed the activity. These features include measures of time elapsed (duration) to complete the activity, and the number of sensor events triggered. See Table 3 for the complete list of extracted features.

We used Neural Networks, a widely used machine learning model, to analyze how well the activity was performed by the participant. Neural networks are mathematical models inspired by the functional aspects of biological neural networks[8]. In this experiment, a multilayer perceptron (MLP) was used. A MLP contains an input layer, one or more hidden layers, and an output layer. Each layer is made up of one or more artificial neural nodes.

We used nine dedicated neural networks to analyze the eight activities – eight neural networks analyze each activity separately, while the ninth neural network analyzes the combined features of all activities. The neural networks were trained with a training set containing activity information of 11 dementia, 3 MCI, and 35 normal participants. A standard back propagation algorithm was used to train the network. After training, the trained neural network was applied to the data from the 28 participants in this study.

Using nine different neural networks, nine different scores were obtained, one for each activity as well as the combined features of all activities. These scores were then averaged to determine a combined functional score for the participant. This method of averaging is commonly known as voting-average[8,9] and is one most common ways to combine multiple machine learning models.

RESULTS

Pearson correlations were used to analyze the relationships between the data obtained through direct observation, laboratory testing and the motion sensors in the smart home testbed. To determine significance, *p*-values were set at .05. Controlling for age, the functional score calculated from the motion sensor data correlated significantly with the direct observation score (r = -.605, p = .005) and the EPT (r = .583, p = .007). The EPT also strongly correlated with the direct observation score (r = -.624, p = .003).

DISCUSSION

The significant correlation between the functional score derived from the sensor data and the direct observation score suggests that there is a positive relationship between these two measures. Thus, a better score derived from direct observation of the participant performing the activity correlates strongly with a higher functional score derived from the sensor data. This suggests that the data obtained from the motion sensors is in strong agreement with the data obtained through direct observation.

The strong correlations between the functional score derived from the sensor data, direct observation measure, and EPT further suggests that while these assessment methods are different in nature, they are all providing information about everyday functioning. Future research will be needed to determine whether information derived from sensor data collected within a smart home can provide accurate and ongoing information regarding an individual's everyday functional status. Such information would allow for the functional status of individuals to be assessed on a daily basis within their home environment and earlier interventions to be initiated.

FIGURE AND TABLES

Figure 1: Smart Home with Motion (M), Item (I) and Door (D) Sensors

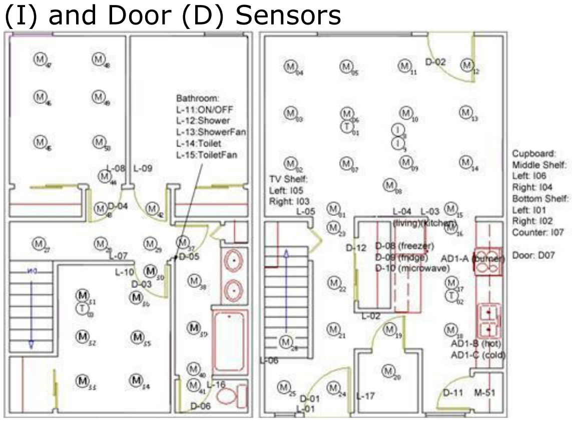

Table 1: Direct Observation Coding Schema

Error Type	Description
Critical Errors	1. <u>Critical Omission</u>: Coded when a step or subtask that is necessary for accurate completion of the activity is not completed (e.g., failure to retrieve broom, failure to put check into envelope). 2. <u>Critical Substitution</u>: Coded when an alternate object, or a correct object but an incorrect gesture, is used and disrupts accurate completion of the activity (e.g., dusting the kitchen instead of the living room, filling medication dispenser incorrectly)
Non-Critical Errors	1. <u>Non-Critical Omission</u>: Coded when a step or subtask is not performed but the activity is still completed accurately (e.g., failure to return items to their original locations, does not turn off the television). 2. <u>Non-Critical Substitution</u>: Coded when an alternate object, or a correct object but an incorrect gesture, is used but the activity is still completed accurately (e.g., uses buttons on television rather than remote to operate electronics, uses container other than watering can to water plants).
Extraneous Errors	1. <u>Irrelevant Action</u>: Coded when an action that is unrelated to the activity, and completely unnecessary for activity completion, is performed (e.g., sweeping the front entryway in addition to the kitchen, washes dishes after completing the cooking task). 2. <u>Inefficient Action</u>: Coded when an action that slows down, or compromises the efficiency of task completion, is performed (e.g., making multiple trips to the dining room table, opening and closing extraneous cupboards and drawers unnecessary for task completion).

Table 2: Direct Observation Score for Each Activity

Score	Description
1	Task completed without any errors
2	Task completed but with no more than 2 of the following errors: non-critical omissions, non-critical substitutions, irrelevant actions, inefficient actions
3	Task completed but with more than 2 of the following errors: non-critical omissions, non-critical substitutions, irrelevant actions, inefficient actions
4	Task incomplete. Coded when a critical omission or substitution occurs and 50% of the task is completed.
5	Task incomplete. Coded when a critical omission or substitution occurs and less than 50% of the task is completed.

Table 3: Features Extracted from Annotated Data

ID	Feature Description
1	Age of Participant (Continuous and Categorized : Young Old, Middle Age, Old Old)
2	Sex
3	Education
4	Was instruction given during activity completion?
5	Were all major sensors triggered during activity completion?
6	Time to initiate activity after direction is given
7	Total number of sensor events generated

8	Number of unrelated sensors that were triggered
9	Total number of unique sensor that were triggered
9	Total count of unrelated sensor values
10	Duration (time) taken to complete the activity
11	Number of item interactions
12	Number of door interactions
13	M0-M25(number of times the different motion sensors were triggered)
14	Activity ID

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REFERENCES

[1] E. Aretouli and J. Brandt, "Everyday functioning in mild cognitive impairment and its relationship with executive cognition," *International Journal of Geriatric Psychiatry*, vol. 25, pp. 224-233, 2010.

[2] T.D. Marcotte, J.C. Scott, R. Kamat, and R.K. Heaton, "Neuropsychology and the prediction of everyday functioning" in T.D. Marcotte & I. Grant (Eds.), *Neuropsychology of everyday functioning,* pp. 5-38, The Guilford Press, New York, 2010.

[3] S.L. Willis, G.M. Jay, M. Diehl, and M. Marsiske, "Longitudinal change and prediction of everyday task competence in the elderly," *Research on Aging,* vol. 14, pp. 68-91, 1992.

[4] T.L. Hayes, F. Abendroth, A. Adamid, M. Payela, T.A. Zitzelberger, and J.A. Kaye, "Unobtrusive assessment of activity patterns associated with mild cognitive impairment," *Alzheimer's & Dementia,* vol. 4, pp. 395-405, 2008.

[5] P. Rashidi, D.J. Cook, L.B. Holder, and M. Schmitter-Edgecombe, "Discovering activities to recognize and track in a smart environment," *accepted to IEEE Transactions on Knowledge and Data Engineering, 2010.*

[6] Petersen, et al. Current concepts in mild cognitive impairment, Archives of Neurology, vol. 58, pp. 1985-1992, 2001.

[7] S. Willis and M. Marsiske, *Manual for the Everyday Problems Test*, Pennsylvania State University Department of Human Development and Family Studies, University Park, Pennsylvania, 1993.

[8] E. Alpaydin. *Introduction to Machine Learning.* MIT Press, Cambridge, Massachusetts, 2010.

[9] Thomas G. Dietterich, Ensemble Methods in Machine Learning, Proceedings of the First International Workshop on Multiple Classifier Systems, 2000.