Consistency and timing in activity recognition across varied populations

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Introduction

The lifespan of the average adult is increasing, which gives rise to a larger and older population. With the expense and emotional strain of age, the healthcare industry is now faced with a serious challenge. How can growing numbers of elderly be cared for in the existing system? One promising option is utilizing "smart environments" as a form of in-home care.

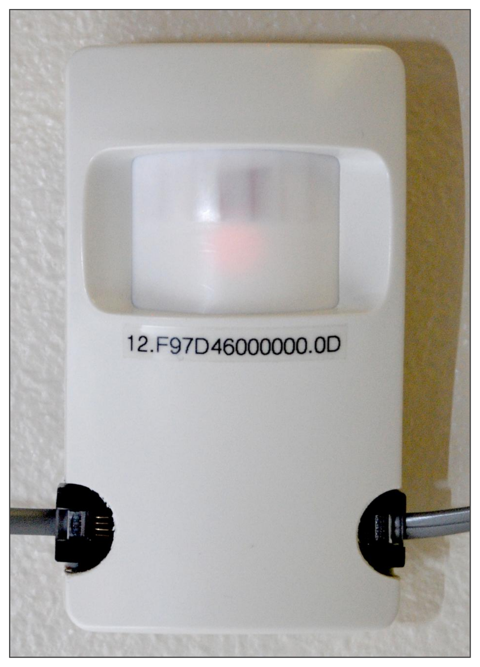
A smart environment combines personal and passive environmental sensors, task recognition and, in some cases, surveillance to determine the conditions of an occupant inside of a residence. Still a developing technology, smart environments suffer obstacles preventing widespread distribution. Among them is the need to refine techniques as applied on a per-user basis. An individual's condition can change with age or illness and multiple occupants in a single location may have different approaches to activities.

This project attempts to address the accuracy of task recognition and the timing of task completion amongst varied populations.

Hypothesis: There may be discernable variations in timing or accuracy of activity recognition in relation to population characteristics.

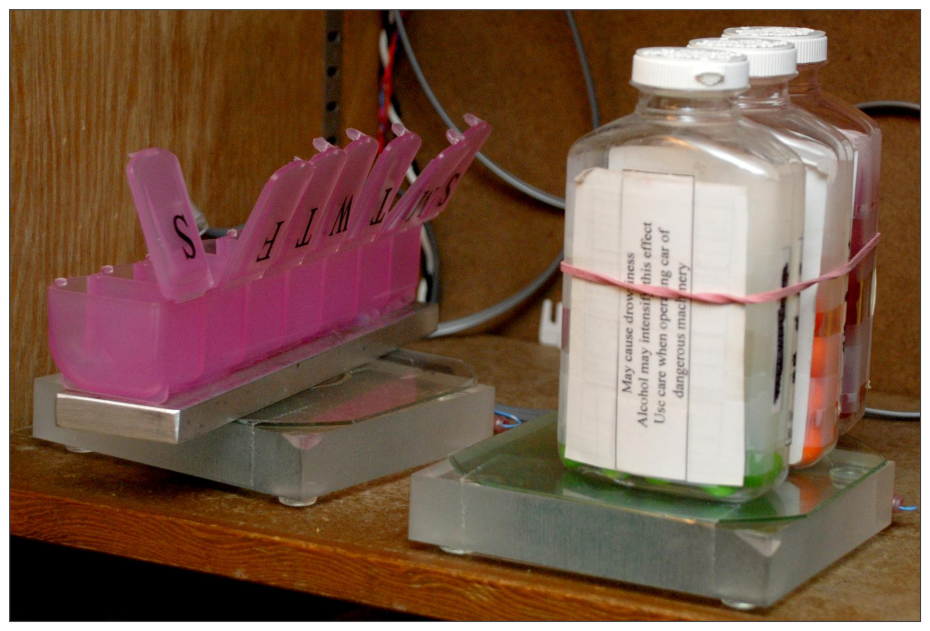
Methods & Materials

Participants in this study were divided into 3 groups (HOA – healthy older adults, HYA – healthy younger adults, Imp – impaired adults) and tested individually. Classification of these participants was based on a series of cognitive tests—a test focusing on Activities of Daily Living (ADL) was the source of data used for this experiment. Participants were asked to complete tasks in a monitored smart apartment, equipped with multiple sensors. For the purposes of this study, only data collected from motion and object sensors were evaluated.



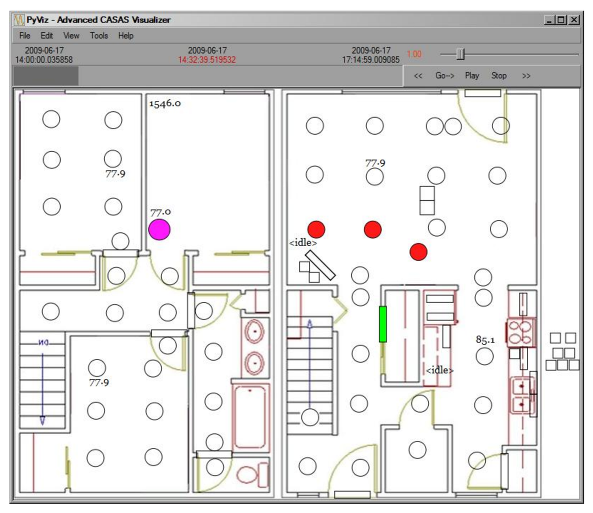
Ceiling-mounted motion sensor from testbed.

Three sets of 8 tasks representing common ADLs, such as cleaning, talking on the phone or preparing a meal, were administered. The first 8 tasks were uncued, while 9 through 16 generated an audio cue for participants who were struggling to complete an activity correctly. Finally, for 17 through 24 participants were encouraged to complete tasks in an inter-woven manner. In instances of test administration error or lack of time, only tasks which were fully completed were examined.

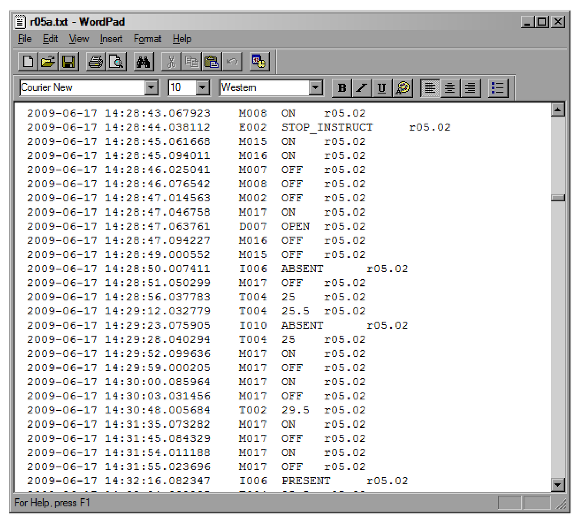


Object interaction sensors inside a kitchen cabinet. Senses the presence or absence of an item, based on small discrepancies in weight.

During cognitive testing, sensor events were automatically saved to a database. Raw sensor data included the date, time, sensor label and state change flag. Using a correlating script of the test procedure, these data were then annotated using PyViz. Sensor events associated with the timeframe indicated for a given task were annotated with a participant and task identification number.



PyViz, used for annotation.



Example of an annotated file.

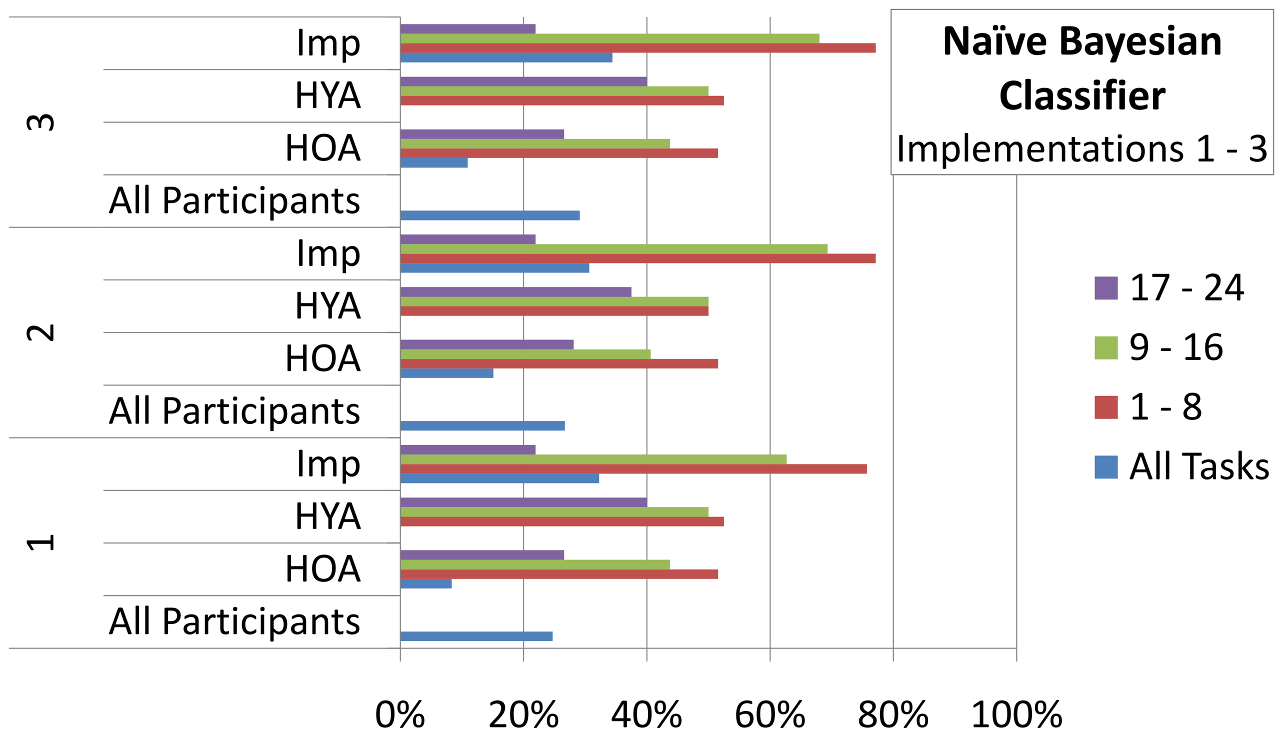
Annotated data was then parsed and used to generate training and testing data sets broken into categories based on participant class and/or the task groups involved. One global file was also generated, which included all tasks and all participant groups.

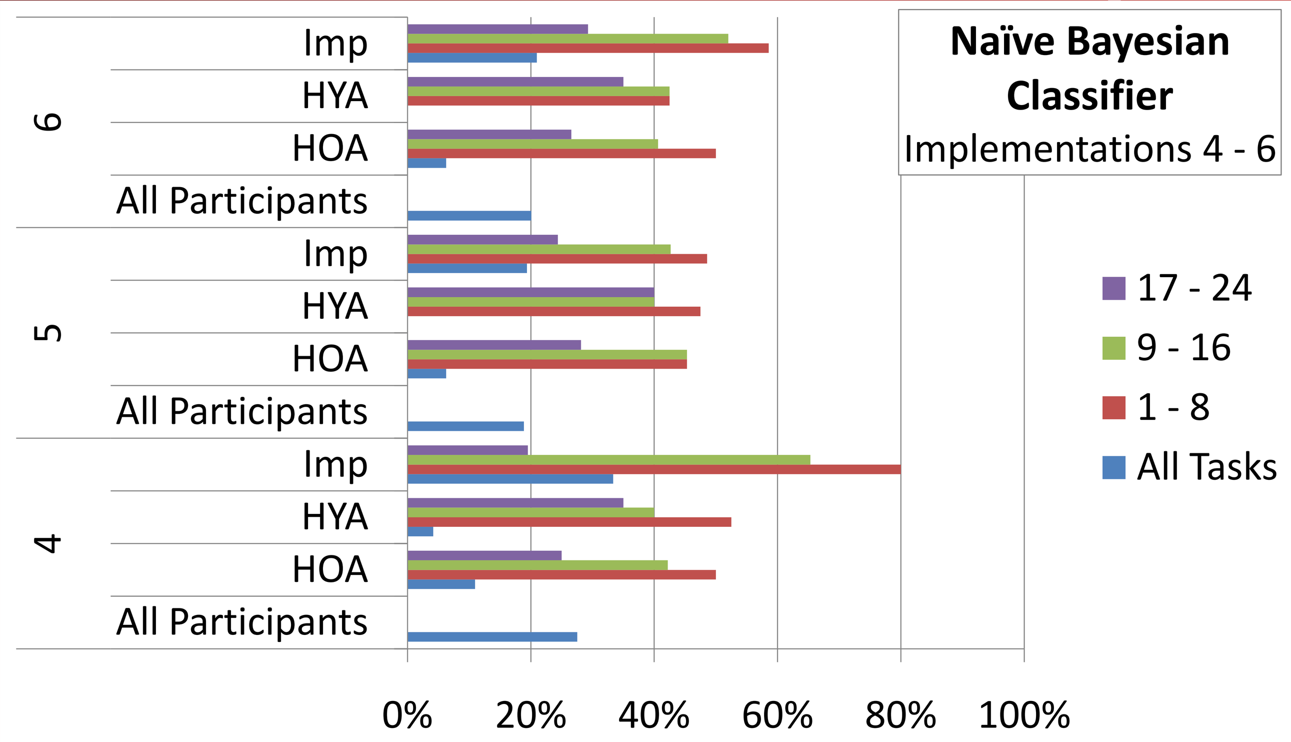
Multiple versions of a basic Naïve Bayesian classifier were built; each rendition implemented a range of features. Considerations included location in the residence, object interaction (presence or absence of an item), time between sensor events, time to complete a task and total sensor events fired. The accuracy of each implementation was tested using three-fold cross-validation. Timing values were also extracted and saved for calculating basic statistics for each participant pool.

Results

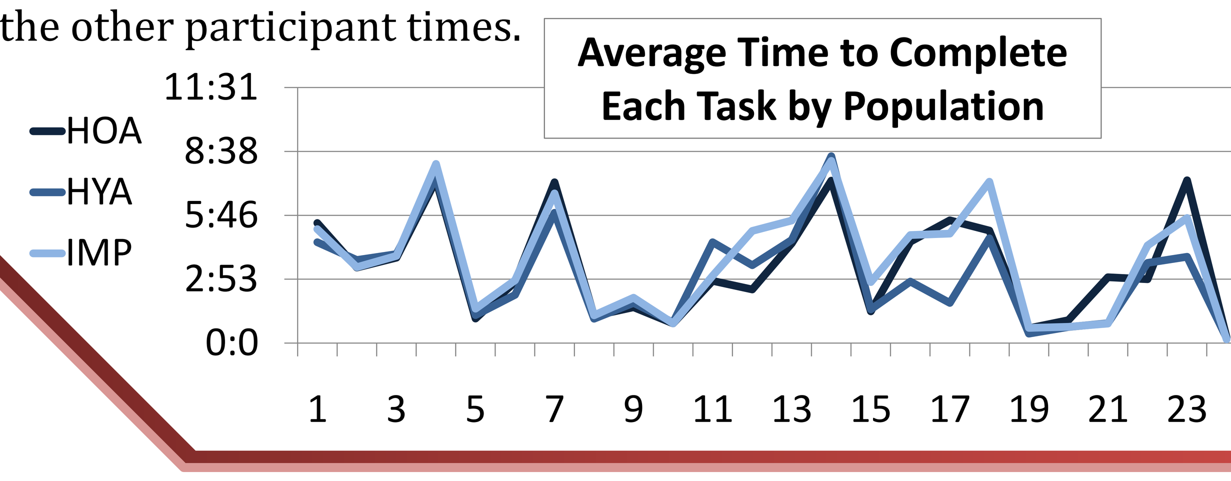
Additional data continue to be incorporated and evaluated as of the production of this poster. Current outcomes indicate differentiable accuracy of task recognition amid participant populations. Statistics from experiments focusing on time do not support a significant distinction between age and/or cognitive characteristics.

Of the 6 implementations of a Naïve Bayesian classifier, impaired adults' tasks were correctly identified with more accuracy every time. In all but 1 implementation, healthy older adults had the lowest average correct identification of tasks. Testing on healthy younger adults yielded an interesting irregularity—this population achieved average results on each set of 8 tasks, but upon testing all 24 tasks at once, accuracy for young adults went as low as 0% in 5 cases and the remaining case reached only 4.17%.





Statistics gathered from time data showed no consistence evidence to support discerning populations based on timing. When comparing average time to complete a task, all 3 groups showed remarkably similar results. In task set 9 through 17, healthy younger adults did show a marked decrease in time necessary to complete certain tasks (12, 15 – 17), but these numbers still shared the same shape (a difference of 1 standard deviation) as the other participant times.



Conclusions

There is a significant link between the accuracy of task recognition and the cognitive level of the subject. It is surprising to find the most accurate results stemming from impaired participants, but it supports the argument that different populations utilize different approaches to task completion. This information may help to determine who is present in a smart environment, which is impactful for the real-world use of this technology.

Potential shortcomings in this study exist and should be addressed in future research. The number of participants tested, particularly healthy younger adults, should be increased. Also, it may be appropriate to further divide participant groups by the nature of their cognitive impairments when running tests. Incorporation of more sensor data, such as door, temperature or electrical readings, would also likely increase the accuracy of the classifier and perhaps sway further results in the correlation between task recognition, timing and discerning populations.

Citing & Acknowledgements

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