



Anomaly Detection of Elderly Patient Activities in Smart Homes using a Graph-Based Approach

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- 13% of the U.S. population in 2013 was of the age 65+ and is estimated to rise to more than 20% by 2030 [1].
- 5.2 million people above the age of 65 have cognitive disabilities like Alzheimer and Dementia [2].
- In 2016, the total annual costs associated with the care of patients with Alzheimer's was estimated at \$236 billion[2].
- This cost is estimated to increase to over \$1 trillion in 2050 [2].



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- Cognitive disabilities can limit person's ability to perform day-to-day activities, requiring them to be dependent on caregivers.
- Smart home sensor systems can provide aid to elderly residents and their caregivers.
- Smart homes can reduce the cost by alleviating some responsibilities on care providers and reducing medical emergencies.



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- The data from smart homes are sensor logs generated while a participant performs daily activities.
- We can convert daily activity logs into a graph by representing a sensor's spatial or temporal information as a node with edges.
- We can search for normal and anomalous patterns in activity graphs.
- We can analyze these patterns to better understand their daily routine.



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- Anomalous behaviors represent possible scenarios where a participant could have a decline in their cognitive ability [3, 4]:
 - **Temporal Anomaly**: Abnormality in duration. Inappropriately long/short period of time to perform a task.
 - **Spatial Anomaly**: Performing activities in the wrong places or wandering around.
 - **Behavior Anomaly**: If the participant violates the expected normal sequence of sub-activities then it is an anomaly.



Research Objective

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- Normal and anomalous patterns in activity graphs helps medical personnel to determine whether a resident is in the early stages of developing cognitive disabilities.
- We formally propose two hypotheses.
Hypothesis I: A graph-based approach can successfully discover anomalies in elderly resident activity in smart homes.
Hypothesis II: Anomalies are potential indicators of a decline in the cognitive health of an elderly resident.



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- Kyoto dataset with 400 participants provided by Washington State University's CASAS program [5].
- Sensor log for each participant, floor-plan layout, and activity information.
- Sensor log has time, sensor identification, sensor value, and an activity number.
- For experimentation, we selected 242 participant(239 healthy & 3 random participants with cognitive impairment).

```
09:21:06.18355 M016 ON
09:21:07.65079 M017 ON 2-start
09:21:08.23585 M014 OFF
09:21:09.5958 M015 OFF
09:21:10.55865 M016 OFF
09:21:11.15833 I006 ABSENT 2.1
09:21:18.67897 M017 OFF
09:21:22.17425 M017 ON 2.2
09:21:23.91058 M017 OFF
09:21:25.33682 I010 ABSENT 2.1
09:21:48.16856 T004 23.5
09:21:48.78192 T002 27
09:21:49.3988 T003 24
09:21:49.99019 T001 23
09:21:50.62013 T005 24.5
09:23:11.77618 P001 1073
09:23:20.74126 P001 1175
09:24:04.75684 P001 1165
09:24:47.62622 M017 ON 2.2
09:24:52.73102 M017 OFF
09:24:58.22623 M017 ON 2.2
09:25:02.45939 M017 OFF
09:25:06.81459 P001 1154
09:25:11.59569 M017 ON 2.2
```

Figure: Sensor Log



Activity Information

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- Data related to eight activities called Instrumental Activities of Daily Living (IADLs)
- Based on a resident's ability to perform IADLs, clinicians can characterize their daily behavior and find out whether they have cognitive or physical difficulties.
- Decline in an ability to perform IADLs is often related to the decline of cognitive ability [6, 7].

1.	Sweep the kitchen and dust the living room.
2.	Obtain a set of medicines and fill medicine dispenser.
3.	Write a birthday card and enclose a check.
4.	Find the appropriate DVD and watch the news clip.
5.	Obtain a watering can and water living room's plant.
6.	Answer the phone and respond to questions.
7.	Prepare a cup of soup using the microwave
8.	Pick a complete outfit for an interview.

Figure: List of activities



Graph Based Anomaly Detection [8]

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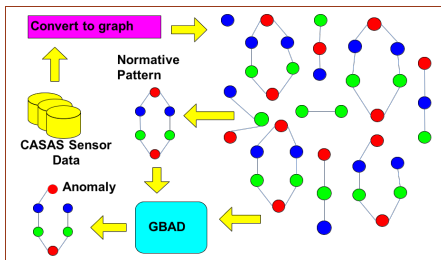
Data

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- $\Pr(SA) = \# \text{ particular SA} / \# \text{ all SA's}$
- Anomaly score = $\Pr(SA) * \text{dist}(SA, S)$
- Possible Anomalies:-
 - Missing nodes/edges (gathered along the way)
 - Additional nodes/edges (search a bit further)
 - Modified labels among structural matches

For more info on GBAD visit (www.gbad.info)



Experimentation

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- Python-based parser tool to construct graph using sensor log files, activities and sensor floor-plan layout.
- Separate graphs (called activity graph) for each of the eight IADL activities for all participants.
- Activity graph 1 (i.e., sweep kitchen and dust living room) is the biggest graph (21,293 vertices and 21,050 edges).
- Activity graph 3 (i.e., write birthday card) is the smallest (only 4367 vertices and 4125 edges).



Graph Layout

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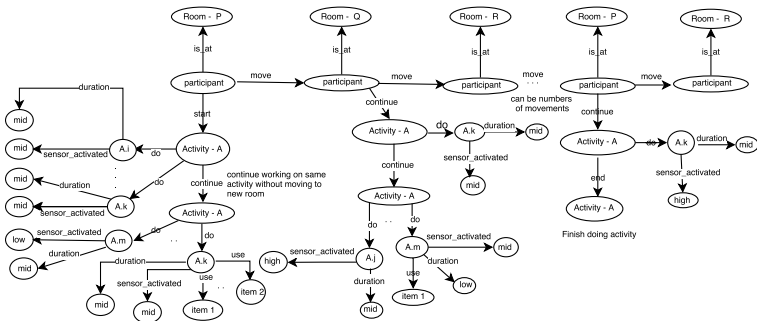


Figure: Graph Layout



Results

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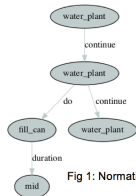


Fig 1: Normative Pattern

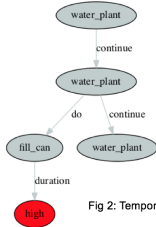


Fig 2: Temporal Anomaly

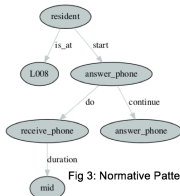


Fig 3: Normative Pattern



Fig 4: Behavioral Anomaly



Fig 5: Normative Pattern

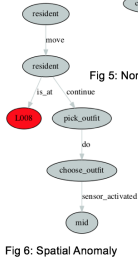


Fig 6: Spatial Anomaly



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TABLE II. GBAD RESULTS FOR PARTICIPANTS P1, P2, AND P3

Activity Graphs	Anomaly		
	Temporal	Spatial	Behavior
1. Sweep kitchen & dust living room	P1,P2,P3		
2. Fill medicine dispenser	P1, P2		
3. Write a birthday card			
4. Watch news clip	P2		
5. Water plants in living room	P2, P3		P2, P3
6. Answer phone	P3		P1
7. Prepare a cup of soup	P1, P2		
8. Choose outfit for an interview	P3	P1,P2,P3	



Discussion

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- Seven activity graphs (beside activity graph 3 i.e. write a birthday card)showed anomalies related to participants P1, P2, and P3.
- The decline in an ability to perform IADLs is often related to the decline of cognitive ability [6, 7].
- Temporal, spatial and behavior anomalies discovered by our experiment are indeed indicators of a decline in cognitive ability.



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- Understanding everyday behavior of elderly resident can be realized using a unsupervised graph-based approach on smart homes activities data.
- Activity graphs are used to find temporal, spatial and behavior anomalies in elderly resident's daily activities.
- We also theorized that these anomalous behaviors represent possible scenarios where a participant could have a decline in cognitive ability.



Future Work

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- Convert real time sensor logs into graph streams and look for anomalies which could be a real-time health monitoring tool.
- Vary the sample and run multiple experiments to see if similar anomalies can be detected.
- Investigate the robustness of the graph topology to see how much the change of graph topology would affect the outcome of our anomaly detection.
- Involve a clinician as a domain expert so that we can validate our results.



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- [1] A. Association *et al.*, "2016 alzheimer's disease facts and figures," *Alzheimer's & Dementia*, vol. 12, no. 4, pp. 459–509, 2016.
- [2] J. M. Ortman, V. A. Velkoff, H. Hogan *et al.*, *An aging nation: the older population in the United States*. United States Census Bureau, Economics and Statistics Administration, US Department of Commerce, 2014.
- [3] C. Zhu, W. Sheng, and M. Liu, "Wearable sensor-based behavioral anomaly detection in smart assisted living systems," *IEEE Transactions on Automation Science and Engineering*, vol. 12, no. 4, pp. 1225–1234, 2015.
- [4] A. C. Tran, S. Marsland, J. Dietrich, H. W. Guesgen, and P. Lyons, "Use cases for abnormal behaviour detection in smart homes," in *International Conference on Smart Homes and Health Telematics*. Springer, 2010, pp. 144–151.
- [5] D. J. Cook, A. S. Crandall, B. L. Thomas, and N. C. Krishnan, "Casas: A smart home in a box," *Computer*, vol. 46, no. 7, pp. 62–69, 2013.
- [6] J. E. Galvin and C. H. Sadowsky, "Practical guidelines for the recognition and diagnosis of dementia," *The Journal of the American Board of Family Medicine*, vol. 25, no. 3, pp. 367–382, 2012.
- [7] S. Martin, G. Kelly, W. G. Kernohan, B. McCreight, and C. Nugent, "Smart home technologies for health and social care support," *Cochrane Database Syst Rev*, vol. 4, no. 2, 2008.
- [8] W. Eberle and L. B. Holder, "Mining for structural anomalies in graph-based data." in *DMIN*, 2007, pp. 376–389.



Thank You

