

Technological solution for early detection of neurodegenerative diseases in a home environment

The case of Alzheimer's Disease

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INTRODUCTION

Context

- Alzheimer's disease (AD) is responsible for approximately **60 to 70% of diagnosed dementia** cases [3]. This disease leads to cognitive decline that disrupt daily life activities [3,4].
- Recent advancements in monitoring and addressing the physical and cognitive states of AD patients hold promise for improving their quality of life [2]. However, most current solutions target patients in advanced disease stages, accompanied by progressive loss of independence [5]. **Few innovations focus on early detection**, especially in the asymptomatic stage, which can take longer than 10 years, when cognitive symptoms are subtle and may resemble normal aging [1].

In France



Source : <https://www.fondation-mederic-alzheimer.org>

Main Objectives

- Designing a home automation monitoring system to remotely and longitudinally monitor changes in both mental and physical states of an individual. The objective is to **detect early signs of neurodegenerative diseases, particularly Alzheimer's Disease (AD)**.
- Respecting the **eco-design perspective**: innovative opportunistic reuse of resources and various household objects existing in the foyer to detect potential indicators while ensuring privacy, confidentiality, and data security.

METHODOLOGY

Multiple exeperimental stages

MACRO LEVEL

Phase 1 – July 2024

- Assess sensor-based system to **detect and classify different types of home behavioral activities** and examine the **acceptability** of the sensors.



MICRO LEVEL

Phase 2 (Upcoming)

- Recognise complex tasks and **integrate more Internet of Things (IoT) devices** and advanced features such as a **chatbot system**.



Phase 3 (Upcoming)

- Test under real-world conditions** by using **long-term evaluation** to assess the system ability to detect subtle changes in user behavior.

Living Lab Imredd



Hypothesis Phase 1

H1: The sensor system is capable of categorizing different types of activity:

- cognitive activities** (e.g., static activities like reading),
- physical activities** (e.g., movements like setting the table),
- inactivity** (resting periods).

H2: The sensor system, even **without video cameras**, can reliably detect different types of activities as accurately as a system with cameras.

July 2024 Test



8 activities of daily living

- 4 Cognitive activities
- 3 Physical activities
- 1 Inactivity (Resting)



5 types of sensors

- Pressure sensors,
- Electric sensors,
- Motion sensors,
- Lightning sensors,
- Cameras



14 participants

- 65% > 60 yr.
- 9 women/5 men
- 2 hours of testing/ person



Analysis tools

- Grafana
- BOWL (Epicnoc)
- ActoGraph
- R Studio & Factoshiny

RESULTS

Activities and sensors activation

Figure 1 :

Activities of one of the participants across various tasks, monitored in real-time.

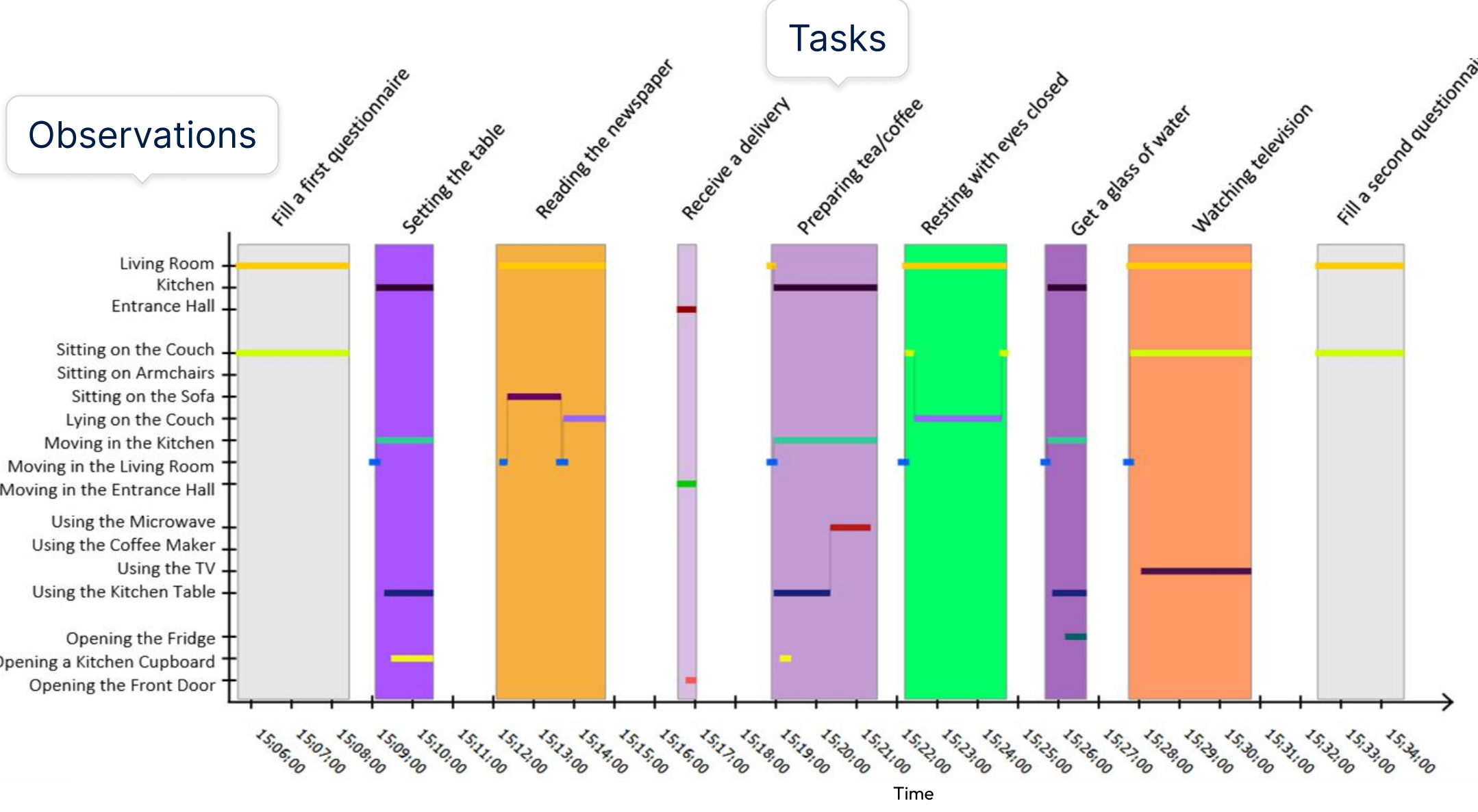
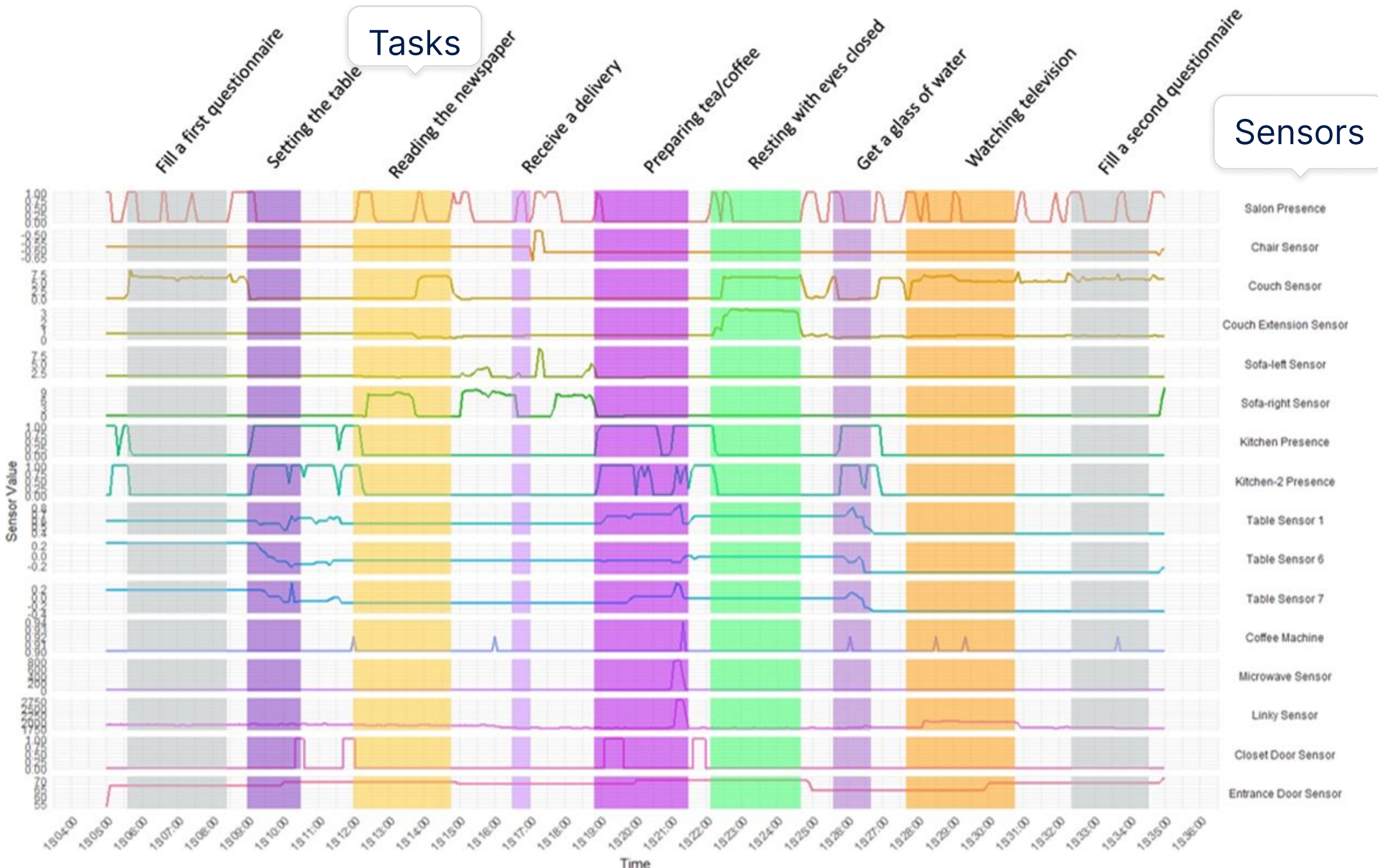


Figure 2 :

Sensor activations data for various tasks performed in the Living Lab during one of the tests.



Statistics - PCA and HCPC

Principal Component Analysis (PCA) was conducted to analyze how sensor activations vary across participants and tasks, while also reducing noise and redundancy of the data.

- By focusing on the most informative features, 10 sensors were selected for their strong discriminative power.
- The variable "Task" emerged as the most significant factor explaining the differences between individuals in the PCA analysis ($p < .001$).

Hierarchical Clustering on Principal Components (HCPC) was applied to identify groups of tasks with similar sensor activation patterns. The clustering **results revealed a strong statistical association between the task clusters and the sensor activation data** ($p < .001$).

- Significant distinction between three main categories of activities. "Inactivity" was strongly associated with sofa and presence sensors ($v = 9.04$, $p < 0.001$), "Cognitive activities" like watching TV and reading were linked to armchair and couch sensors ($v = 3.44$, $p < .001$), and "Physical activities" such as setting the table and preparing drinks correlated with presence, table, and electric sensors ($v = 5.13$, $p < .001$).

DISCUSSION

General Discussion

The main objectives of the first experimental phase were:

- to evaluate whether sensor-based systems could accurately **classify various daily activities**,
- to **detect specific sensor activation patterns** for each activity,
- to compare these sensor patterns with camera-based behavioral observations.

The main results revealed strong similarities between the behaviors observed using cameras and sensor activation during each task. The **different tasks generate distinct sensor activation patterns**, that supports the hypothesis that sensor patterns can reliably differentiate between daily activities.

Moreover, PCA and HCPC analyses provided quantitative validation of these observations.

- According to PCA, **"Task" variable explained most of the variability** in sensor data, emphasizing a strong link between sensor activation and task type.
- HCPC clustering reinforced these findings by revealing **three distinct activity groups—cognitive, physical, and inactive**—each statistically linked to specific sensor activation profiles.

Thus, both hypotheses were corroborated by the analysis, demonstrating the effectiveness of sensors in activity classification.

Limitation

Key limitation of our study is the minimal variability observed among participants, despite the wide age range spanning from 40 to 80 years.

This limited variation may be attributed to the **small number of sensors**. A more extensive sensor-based system could allow for the capture of a broader range of behaviors, especially in more complex or overlapping tasks, providing a more comprehensive view of daily activity patterns.

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