

Generalized Linear Models of Home Activity for Automatic Detection of Mild Cognitive Impairment in Older Adults*

Ahmad Akl¹ and Jasper Snoek² and Alex Mihailidis³

Abstract—With a globally aging population, the burden of care of cognitively impaired older adults is becoming increasingly concerning. Instances of Alzheimer’s disease and other forms of dementia are becoming ever more frequent. Earlier detection of cognitive impairment offers significant benefits, but remains difficult to do in practice. In this paper, we develop statistical models of the behavior of older adults within their homes using sensor data in order to detect the early onset of cognitive decline. Specifically, we use inhomogenous Poisson processes to model the presence of subjects within different rooms throughout the day in the home using unobtrusive sensing technologies. We compare the distributions learned from cognitively intact and impaired subjects using information theoretic tools and observe statistical differences between the two populations which we believe can be used to help detect the onset of cognitive decline.

Index Terms — *Mild Cognitive Impairment, Unobtrusive Sensing Technologies, Older Population, Generalized Linear Models, Poisson Distribution*

I. INTRODUCTION

Alzheimer’s disease is the sixth leading cause of death in North America [1]. Statistics show that one in nine Americans, and one in eleven Canadians, aged 65 and older have Alzheimer’s disease [2]. As the “baby boomer” generation ages, both the proportion and number of older adults with dementia is projected to increase dramatically, thus greatly increasing the burden of care. Early detection of the cognitive decline that precedes dementia is considered to be of great significance for many reasons. For subjects with remediable causes such as nutritional deficiencies or complications resulting from taking medication, early detection of cognitive decline can significantly increase the chances of recovery and prevent further decline. For subjects with irreversible conditions, early detection of cognitive decline still provides them and their families with an opportunity to proactively plan for their future by seeking the appropriate interventions that can enhance their daily functioning and reduce any emotional stress or fear [3].

*This work was supported by P30AG024978 Oregon Roybal Center for Translational Research on Aging, P30AG008017 Oregon Alzheimer’s Disease Center, R01AG024059 BRP, ISAAC Intelligent Systems for Assessing Aging Changes, and Intel Corporation BRP.

¹A. Akl is with the Institute of Biomaterials and Biomedical Engineering, University of Toronto, Toronto, ON M5S 3G9, Canada ahmad.akl at utoronto.ca

²J. Snoek is with the Harvard School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02138, USA jsnoek at seas.harvard.edu

³A. Mihailidis is with the Institute of Biomaterials and Biomedical Engineering, University of Toronto, Toronto, ON M5S 3G9, Canada alex.mihailidis at utoronto.ca

Early stage cognitive decline is challenging to detect in the context of traditional doctor visits, as many of the subtle clues are difficult to spot. However, recent studies have shown that early changes in motor capabilities precede and may be indicative of a cognitive impairment [4], and that subjects with mild cognitive impairment exhibit a more variable and less consistent pattern of activity throughout the day [5]. Accordingly, and with the advancement in technology and the proliferation of smart systems, a good alternative to the traditional clinical paradigm is to bring assessment into the daily activity of a person in their home environment via unobtrusive sensors and smart systems.

Numerous smart systems have been developed to monitor the health and well-being of older adults and support their independence [6] [7]. However, these systems monitor the general health of the inhabitants and are not designed to detect cognitive changes. Other systems, such as [8], have been designed to monitor cognitive changes using a number of predefined measures extracted from sensors. However, this approach has been demonstrated to generalize poorly to new subjects and instead focuses on idiosyncratic nuances of the individual subjects [9].

To address this main issue, in this paper we develop statistical models of the subjects’ general activity in their homes by modeling the distribution of their arrival times at each room as independent inhomogenous Poisson processes. The resulting generalized linear models provide an intuitive statistical analysis and are hypothesized to generalize better to unseen subjects. We develop these models using sensor and clinical data pertaining to 68 subjects, that we received from the OREGON Center for Aging and TECHNOLOGY (OR-CATECH). We take an information theoretic approach and use the KL-divergence measure to compare models pertaining to cognitively intact and impaired subjects. Intuitively, we postulate that there is a statistical difference in the distribution of arrival times between cognitively intact and impaired subjects.

The rest of the paper is organized as follows: Section II explains the data and how it was acquired. Section III describes our approach in building generalized linear models of home activity. Section IV presents and discusses preliminary results. Section V proposes potential future work and Section VI concludes the paper.

II. DATA ACQUISITION & LABELING

All data acquisition was done by ORCATECH who deployed sensing technologies in the homes of at least 300

subjects and monitored them unobtrusively for an average period of 3 years.

A. Participants and Data Acquisition

Participants were recruited from the Portland, Oregon, metropolitan area. The eligibility criteria included:

- 1) being a man or woman aged 80 years or older;
- 2) living independently in a larger than one-room “studio” apartment;
- 3) cognitively healthy (Clinical Dementia Rating (CDR) score < 0.5 ; Mini-Mental State Examination (MMSE) score > 24); and,
- 4) in average health for age (well-controlled chronic diseases and comorbidities or none at all).

Data were acquired by installing sensing technologies in the homes of the recruited subjects. In order to detect movement and general activity, passive infra-red motion sensors were installed in rooms frequently visited by the participating subjects. Visitors and absences from the home were tracked through wireless contact switches placed on the exit doors of the home. All sensor firings were sent wirelessly to a transceiver, time-stamped and recorded. For full details on data acquisition, the reader is referred to [10].

B. Labeling of Data

Participants were assessed in-home at baseline, and during annual in-home visits by research personnel who administered a standardized battery of tests, including the Mini-Mental State Examination (MMSE) and the Clinical Dementia Rating (CDR). CDR served as our ground truth and was used to determine if subjects were cognitively impaired or intact. A score of 0 on the CDR scale indicated cognitive intactness whereas a score of 0.5 on the CDR scale indicated mild cognitive impairment (MCI). Since subjects were assessed annually, data labeling fell into three categories:

- 1) cognitively intact (CIN),
- 2) in-flux or transitioning (IF), and
- 3) transitioned to mild cognitive impairment (MCI).

The labeling protocol that we implemented in assigning labels to the data is summarized in the example depicted by Fig. 1, which represents a subject who was monitored for at least 3 years and was administered three annual assessments besides baseline. The subject scored 0 on CDR

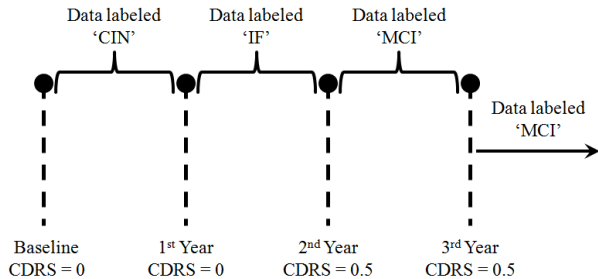


Fig. 1. Example of a subject who scored 0.5 on CDR scale on the 2nd year assessment onward.

scale at baseline, but scored 0.5 on the 2nd and 3rd year assessments. Therefore, the data from baseline up to the 1st year assessment were assigned the label ‘CIN’ and the data from the 2nd year assessment onward were assigned the label ‘MCI’. The data between the 1st year and the 2nd year assessments were assigned the label ‘IF’. This is because the conversion to cognitive impairment is not an instantaneous event but a very gradual process. Accordingly, the subject’s cognitive status would be in flux between years 1 and 2 and would belong to neither cognitive intactness nor MCI.

III. PROBLEM SETUP

In this section, we represent variables by lower case letters, e.g. u , vectors by bold lower case letters, e.g. \mathbf{u} , and matrices by bold upper case letters, e.g. \mathbf{U} . Suppose that a database consists of N subjects, each subject residing in a living unit with n rooms, and we are interested in building statistical models for each subject that would estimate the probability of the subject being present in a room within a fixed time interval throughout the day. Accordingly, the problem can be well-modeled as a Poisson process, because a Poisson distribution models the number of occurrences of an event in a fixed period of time. In our case, the event is being present in a room. By defining a binary variable, y , that indicates absence ($y = 0$) or presence ($y = 1$) in a room, the probability of a subject arriving at a room can be given by

$$p(y) = \frac{e^{-\lambda} \lambda^y}{y!} \quad (1)$$

where λ is the Poisson distribution parameter.

However, note that in this problem, parameter λ would most likely vary throughout the day as the presence in each room is highly time dependent, and therefore an inhomogeneous Poisson process would be a better model. To address the inhomogeneity, we divide a day into k intervals and define a λ_i for each interval where $1 \leq i \leq k$. Therefore, a day represented by a matrix \mathbf{X} would look like the following:

$$\mathbf{X} = [\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \dots, \mathbf{x}^{(i)}, \dots, \mathbf{x}^{(k)}], \quad (2)$$

where,

$$\mathbf{x}^{(i)} = x_j \text{ for } 1 \leq j \leq k \text{ s.t. } \begin{cases} x_j = 1 & i = j \\ x_j = 0 & i \neq j. \end{cases} \quad (3)$$

In other words, \mathbf{X} takes the form of an identity matrix of size $k \times k$, where each column represents a time interval, and each interval is associated with a λ_i . Consequently, if a subject was monitored for 900 days for example, then the subject’s input space would consist of a total number of $m = 900 \times k$ vectors. Each vector would have a corresponding label y indicating whether the subject was present in the room during this time interval or not.

Accordingly, the problem becomes that of estimating the probability of a subject being present in a room given a time interval $\mathbf{x}^{(i)}$ as an input. To do that, we need to find the λ_i ’s corresponding to each interval, which we will represent by the vector $\boldsymbol{\lambda}$. Accordingly, each room will be associated with a $\boldsymbol{\lambda}$ vector. Therefore, given a data set of m time intervals

along with the corresponding labels represented by the vector $\mathbf{y} = \{y^{(i)}\}_{i=1}^m$, the goal is to find $\boldsymbol{\lambda}$ that would maximize the likelihood function $L(\mathbf{y}|\boldsymbol{\lambda})$,

$$L(\mathbf{y}|\boldsymbol{\lambda}) = \prod_{i=1}^m \frac{e^{-\lambda_i} \lambda_i^{y^{(i)}}}{y^{(i)}!}. \quad (4)$$

However, maximizing (4) is equivalent to maximizing its log. Therefore,

$$\begin{aligned} \ell(\boldsymbol{\lambda}) &= \log(L(\mathbf{y}|\boldsymbol{\lambda})) \\ &= \log \prod_{i=1}^m \frac{e^{-\lambda_i} \lambda_i^{y^{(i)}}}{y^{(i)}!} \\ &= \sum_{i=1}^m \log \frac{e^{-\lambda_i} \lambda_i^{y^{(i)}}}{y^{(i)}!} \\ &= \sum_{i=1}^m -\lambda_i + y^{(i)} \log \lambda_i - \log(y^{(i)}!). \end{aligned} \quad (5)$$

As has been demonstrated and proven in [11], to estimate λ originating from an inhomogenous Poisson process, λ should be defined as a function that is monotonic, grows at least linearly, decays exponentially, and has a derivative. λ_i of the form $e^{\mathbf{x}^{(i)T} \mathbf{w}}$ meets these constraints, and consequently, the problem of finding $\boldsymbol{\lambda}$ turns into the problem of finding the weight vector \mathbf{w} . Substituting this definition of λ_i in (5), we get

$$\ell(\mathbf{w}) = -\sum_{i=1}^m e^{\mathbf{x}^{(i)T} \mathbf{w}} + \sum_{i=1}^m y^{(i)} \mathbf{x}^{(i)T} \mathbf{w} - \sum_{i=1}^m \log(y^{(i)}!) \quad (6)$$

But since $y^{(i)}$ is binary, then $y^{(i)}!$ is always equal to 1 which in turn means that $\log(y^{(i)}!)$ is always equal to 0. Accordingly, (6) becomes

$$\ell(\mathbf{w}) = -\sum_{i=1}^m e^{\mathbf{x}^{(i)T} \mathbf{w}} + \sum_{i=1}^m y^{(i)} \mathbf{x}^{(i)T} \mathbf{w} \quad (7)$$

Maximizing (7) is equivalent to minimizing the negative of it, i.e., minimizing

$$\ell'(\mathbf{w}) = -\ell(\mathbf{w}) = \sum_{i=1}^m e^{\mathbf{x}^{(i)T} \mathbf{w}} - \sum_{i=1}^m y^{(i)} \mathbf{x}^{(i)T} \mathbf{w} \quad (8)$$

whose derivative is given by

$$\frac{d\ell'(\mathbf{w})}{dw_j} = \sum_{i=1}^m x_j^{(i)} e^{\mathbf{x}^{(i)T} \mathbf{w}} - \sum_{i=1}^m y^{(i)} x_j^{(i)} \quad (9)$$

Once \mathbf{w} is found, $\boldsymbol{\lambda}$ is computed as $\boldsymbol{\lambda} = e^{\mathbf{w}}$. Therefore, for a subject residing in a living unit with 5 rooms for example, who transitioned to MCI during the study, we would need to approximate 15 $\boldsymbol{\lambda}$ vectors, one for each room for when the subject is cognitively intact, when the subject's cognition is in flux, and when the subject is cognitively impaired.

IV. PRELIMINARY RESULTS

Of the 68 subjects, 7 were males and 61 were females. Of the male subjects, 2 transitioned to MCI during the monitoring period, and of the female subjects, 13 transitioned to MCI during the monitoring period. In this section, we

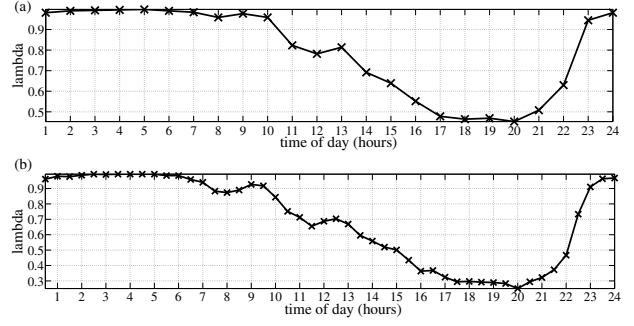


Fig. 2. a) Bedroom distribution for a subject estimated using hourly intervals. b) Bedroom distribution for the same subject estimated using 30-minute intervals.

report preliminary results by building generalized linear models corresponding to four rooms: bedroom, bathroom, kitchen, and living room since these rooms exist in all houses and living units of any size. Accordingly, for each subject we estimated four Poisson distributions (λ_{bdr} , λ_{br} , λ_k , and λ_{lr}) for each stage of cognition (cognitive intactness, in-flux or transitioning, and MCI). According to (1), for $y = 1$ the probability is directly proportional to λ . Therefore, a high λ is equivalent to a high probability.

Initially, we developed these models for a number of subjects in order to determine the best k , the number of time intervals per day. Fig. 2a) shows the bedroom distribution for a cognitively intact subject using hourly intervals ($k = 24$) whereas Fig. 2b) shows the distribution using 30-minute intervals ($k = 48$). As Fig. 2 shows, the distribution estimated using 30-minute intervals appears smoother than the distribution estimated using hourly intervals. Intuitively, the shorter the interval length the smoother the distribution, but the higher the computational cost. However, the smoothness portrayed by Fig. 2b) was satisfactory and therefore, the rest of the results are based on $k = 48$ intervals.

Fig. 3 depicts the bedroom distributions pertaining to a subject who transitioned to MCI during the monitoring period, where Fig. 3a) shows the distribution corresponding to the stage of cognitive intactness, Fig. 3b) shows the dis-

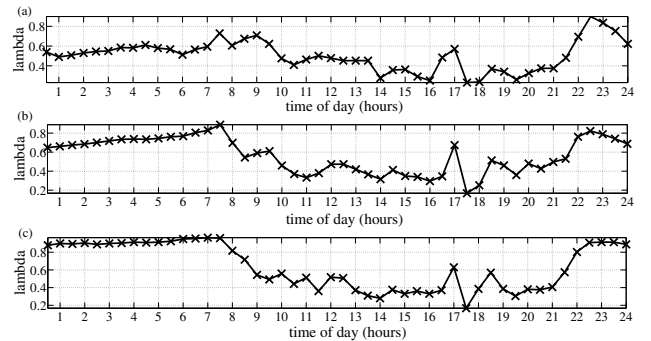


Fig. 3. a) Bedroom distribution for a subject when cognitively intact. b) Bedroom distribution for the same subject when transitioning or in-flux. c) Bedroom distribution for the subject when cognitively impaired.

tribution corresponding to the stage of transitioning to MCI, and Fig. 3c) shows the distribution corresponding to the stage of MCI. From these distributions, we are able to visualize how likely the subject is to be present in the bedroom throughout the day. Furthermore, using these distributions, and distributions pertaining to other subjects who transitioned to MCI, we were able to extract important differences among the three distributions. One main observation was the distributions pertaining to the cognitive intactness stage were smoother than the distributions pertaining to the transitioning and the MCI stages. This is apparent in Fig. 3.

Another important observation was that we were able to extract few MCI symptoms such as disturbed sleep patterns which is clearly portrayed by the distributions in Fig. 3. Because the motion sensors utilized in this study were passive infra-red sensors, then they would fire only when the subject is actively present. Sleeping would not be detected by these sensors and that explains the low probability from 11PM - 7AM when the subject was cognitively intact. However, as the subject started transitioning to MCI, the probability of being present in the bedroom from 11PM - 7AM increased, and increased the most when the subject transitioned to MCI. This increase in probability of presence was potentially due to movements and activity related to disturbed sleep patterns which have been proven to be associated with MCI [12].

Finally, by taking an information theoretic approach, we computed the kl-divergence measure, which is a measure of difference, between the cognitive intactness and the transitioning distributions, between the cognitive intactness and MCI distributions, and between transitioning and MCI distributions for all subjects as depicted in Fig. 4. As shown in Fig. 4, an increasing trend is portrayed as we move from cognitive intactness to transitioning to MCI which implies that when subjects are transitioning, they exhibit behaviors and patterns closer to MCI than cognitive intactness.

V. FUTURE WORK

Based on these promising results, for future work, we plan to further explore this approach by eliciting differences between cognitively intact models and cognitively impaired models using other metrics, such as entropy. Furthermore,

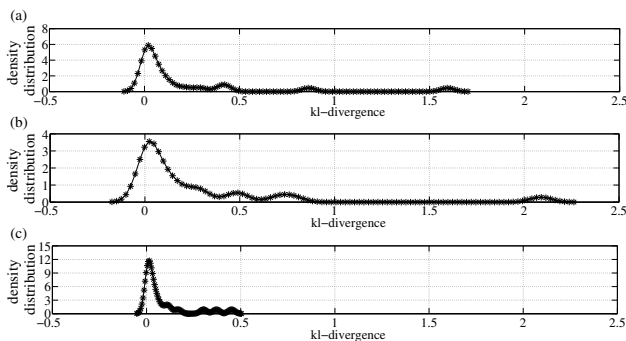


Fig. 4. Distributions of kl-divergence measures between a) cognitive intactness and transitioning distributions, b) cognitive intactness and MCI distributions, and c) transitioning and MCI distributions.

since the clinical field is not a bastion of clarity on the definition of MCI [13], we plan to experiment with a set of neuropsychological assessments as our ground truth instead of CDR and compare the results. Finally, we also plan to explore augmenting these models with other features such subjects' age, gender, and the number of times a subject visits a room instead of a binary presence or absence.

VI. CONCLUSION

In this paper we presented an alternative approach to that of existing studies on smart systems developed to monitor cognitive decline. Our simple approach is more generalizable than existing approaches which tend to overfit the data from individual subjects. We developed a statistical model of the presence of a subject within a room as an inhomogeneous Poisson process. We built generalized linear models for four rooms - bedroom, bathroom, kitchen, and living room - using data from 68 subjects, 15 of which transitioned to MCI during the monitoring period. Most importantly, using the learned models, we were able to observe statistical differences between the behavior of cognitively impaired and intact subjects that could potentially assist in the early detection of cognitive impairment and dementia.

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