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Estimating In-home Walking Speed Distributions for Unobtrusive Detection of Mild Cognitive Impairment in Older Adults*

Ahmad Akl [Student Member, IEEE] and Alex Mihailidis

Ahmad Akl: ahmad.akl@utoronto.ca; Alex Mihailidis: alex.mihailidis@utoronto.ca

Abstract

Timely recognition of cognitive impairment such as Alzheimer's disease is of great significance. Many smart systems, developed to continuously monitor subjects' health and cognition, use a number of predefined measures associated with the subjects' activity in their homes. However, this approach has been demonstrated to focus on the idiosyncratic nuances of the individual subjects and thus could potentially not perform as well on new subjects. In this paper, we address this problem by building proper statistical models of the subjects' in-home walking speed. Using the data pertaining to 15 older adults monitored for an average period of 3 years, we used linear regression with a Gaussian likelihood to model the in-home walking speed of the subjects, and we used dynamic time warping to demonstrate significant difference between the walking speed distributions of the subjects when cognitively intact and when suffering from MCI. Using a simple thresholding approach of the dynamic time warping costs, we were able to detect MCI in older adults with an area under the ROC curve and an area under the precision-recall curve of 0.906 and 0.790, respectively, using a time frame of 12 weeks.

I. Introduction

Alzheimer's disease, the most common cause of Dementia, is a fatal disease that eventually affects a person's ability to think, make decisions, and perform simple daily tasks such as eating, bathing, and getting dressed [1]. 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 on the healthcare infrastructure. The contemporary detection process, in the form of traditional doctor visits, has resulted in a high under-recognition rate of dementia since many of the subtle clues are difficult to spot. Accordingly, with the changing demographic, early detection of the cognitive decline that precedes dementia becomes imperative. For subjects with remediable causes such as medication complications or nutritional deficiencies, early detection of cognitive decline renders timely intervention possible increasing the chances of reversing the condition. 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 and support [2].

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Mild cognitive impairment (MCI) is a condition in which an individual has measurable changes in thinking abilities, but are not significantly severe to impact the individual's ability to carry out activities of daily living. According to the proposed criteria and guidelines for diagnosis of Alzheimer's disease published in 2011, in many cases mild cognitive impairment (MCI) is an early stage of Alzheimer's or dementia [3]. Therefore, detecting MCI serves the goal of early detection of cognitive impairment. Recent studies have shown that early changes in motor capabilities precede and may be indicative of a cognitive impairment [4], and that changes in walking speed can serve as good measures to differentiate older adults with MCI and to be good predictors of progression to dementia [5].

Building on these studies, we previously explored the feasibility of autonomously discriminating older adults with MCI from their cognitively intact counterparts using a number of predefined measures associated with the subjects' in-home walking speed [6]. Different time frames were used to extract features from the predefined measures which were then used to train and test two machine learning algorithms, namely support vector machines and random forests. Despite the high sensitivity and specificity scores reported, we demonstrated that such a method of using predefined measures is susceptible to focusing on idiosyncratic nuances of the individual subjects and therefore, could potentially generalize poorly to new subjects. To address this problem, in this paper we propose a novel approach in developing statistical models of subjects' in-home walking speed. We use linear regression with a Gaussian likelihood to build generalized linear models of the subjects' in-home walking speed. The resulting models provide intuitive statistical analysis and are hypothesized to generalize better to new subjects.

The rest of the paper is organized as follows: Section II explains the data and how they were acquired. Section III describes our approach in building generalized linear models of in-home walking speed. Section IV presents and discusses preliminary results. Section V concludes the paper by proposing directions for future work.

II. DATA ACQUISITION & LABELING

All data acquisition was done by the OREGON Center for Aging and TECHNOlogy (ORCATECH) who deployed sensing technologies in the homes of many older adults and monitored them continuously for several years.

A. Participants and Data Acquisition

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

1. being a man or woman aged 70 years or older;
2. living independently in a one-room "studio" apartment or larger; and,
3. cognitively healthy (Clinical Dementia Rating (CDR) score < 0.5) and in average health for age.

Data were acquired by installing motion sensing technologies in the homes of the recruited subjects. Walking speeds were estimated unobtrusively by placing motion sensors on the

ceiling approximately 61 cm apart in areas such as a hallway or a corridor. These sensors had a modified field view restricted to $\pm 4^\circ$ so that they would only fire when someone passed directly under them. A detailed description of how the walking speed was estimated is fully described in [7] [8]. All sensor firings were communicated wirelessly to a transceiver, where they were time stamped, and then stored in an SQL database.

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. Clinical Dementia Rating (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. transitioning to MCI (TR), and
3. suffering from MCI (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 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 'TR'. This is because the conversion to cognitive impairment is not an instantaneous event but a gradual process. Accordingly, the subject's cognitive status would be in flux between years 1 and 2 and would not belong to 'CIN' or 'MCI'.

III. Walking Speed Distribution Estimation

In this section, we represent variables by lower case letters, e.g. u , vectors by bold lower case letters or symbols, e.g. $\mathbf{u}$ or $\boldsymbol{\theta}$, and matrices by bold upper case letters, e.g. $\mathbf{U}$. Suppose that for a subject, who has been monitored for a long period of time, we are interested in building a walking speed distribution that would provide an estimate of their walking speed during different time intervals in a day. If we divide the day into K equal intervals, then a day can be represented by a $K \times K$ identity matrix $\mathbf{X}$, defined as follows:

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

where $1 \leq i \leq K$ and each column $\mathbf{x}^{(i)}$, defined as,

$$\mathbf{x}^{(i)} = x_{j s.t.} \begin{cases} x_j = 1 & \text{if } i = j \\ x_j = 0 & \text{if } i \neq j, \end{cases} \quad (2)$$

represents a time interval, and $j = 1, \dots, K$. According to this formulation, the goal is then to estimate the walking speed, $ws^{(i)}$, associated with each time interval $\mathbf{x}^{(i)}$ for each subject. One way to relate the walking speed to the time intervals is via the following equation,

$$ws^{(i)} = \boldsymbol{\theta}^T \mathbf{z}^{(i)} + \boldsymbol{\varepsilon}^{(i)} \quad (3)$$

where $\boldsymbol{\varepsilon}^{(i)}$ is an error term that captures random noise associated with each interval, $\boldsymbol{\theta} = [\theta_0, \theta_1, \dots, \theta_K]$ is a $(K+1)$ weight vector that needs to be determined in order to estimate the walking speed, and,

$$\mathbf{z}^{(i)} = \begin{bmatrix} 1 \\ \mathbf{x}^{(i)} \end{bmatrix}. \quad (4)$$

This formulation meets our objective because it minimizes the error between the estimated walking speed per interval and the actual walking speed for each subject. If we further assume that the $\boldsymbol{\varepsilon}^{(i)}$'s are distributed IID according to a Gaussian distribution, then the distribution of the walking speed parameterized by $\boldsymbol{\theta}$ is given by,

$$p(ws^{(i)} | \mathbf{z}^{(i)}; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left(-\frac{(ws^{(i)} - \boldsymbol{\theta}^T \mathbf{z}^{(i)})^2}{2\sigma^2} \right). \quad (5)$$

Then for a subject with m input vectors, the goal is to find the $\boldsymbol{\theta}$ vector that maximizes the likelihood function $L(\boldsymbol{\theta})$,

$$L(\boldsymbol{\theta}) = \prod_{s=1}^m p(ws^{(s)} | \mathbf{z}^{(s)}; \boldsymbol{\theta}) = \prod_{s=1}^m \frac{1}{\sqrt{2\pi}\sigma} \exp \left(-\frac{(ws^{(s)} - \boldsymbol{\theta}^T \mathbf{z}^{(s)})^2}{2\sigma^2} \right) \quad (6)$$

which is equivalent to maximizing its log. Therefore,

$$\begin{aligned} \ell(\boldsymbol{\theta}) &= \log \prod_{s=1}^m \frac{1}{\sqrt{2\pi}\sigma} \exp \left(-\frac{(ws^{(s)} - \boldsymbol{\theta}^T \mathbf{z}^{(s)})^2}{2\sigma^2} \right) \\ &= \sum_{s=1}^m \log \frac{1}{\sqrt{2\pi}\sigma} \exp \left(-\frac{(ws^{(s)} - \boldsymbol{\theta}^T \mathbf{z}^{(s)})^2}{2\sigma^2} \right) \\ &= C - \frac{1}{\sigma^2} \cdot \frac{1}{2} \sum_{s=1}^m (ws^{(s)} - \boldsymbol{\theta}^T \mathbf{z}^{(s)})^2 \end{aligned} \quad (7)$$

where $C = m \log \frac{1}{\sqrt{2\pi}\sigma}$. According to (7), the weight vector $\boldsymbol{\theta}$ is found by minimizing

$$\ell'(\boldsymbol{\theta}) = \frac{1}{2} \sum_{s=1}^m (ws^{(s)} - \boldsymbol{\theta}^T \mathbf{z}^{(s)})^2. \quad (8)$$

Once θ is found, the walking speeds, $ws^{(i)}$, that form the walking speed distribution $\mathbf{ws} = [ws^{(1)}, ws^{(2)}, \dots, ws^{(K)}]$ are estimated as

$$ws^{(i)} = \theta_0 + \theta_i. \quad (9)$$

IV. Preliminary Results

In this section, we present preliminary results based on walking speed data pertaining to 15 subjects who have been monitored for an average of 3 years, and who transitioned to MCI during the monitoring period. For each subject, the entire “CIN” speed data were used to estimate “CIN” $\mathbf{ws}$, the entire “TR” speed data were used to estimate “TR” $\mathbf{ws}$, and the entire “MCI” speed data were used to estimate “MCI” $\mathbf{ws}$, using $K = 48$ intervals, i.e. 30-minute intervals. Since subjects were less likely to walk under the line of sensors, mounted to measure walking speed, between the hours 12AM and 6AM, we focused on analyzing walking speed activity between 6AM and 12AM.

Fig. 2 shows the walking speed distribution of a male subject, residing in a one-bedroom apartment. The line of sensors used to measure the walking speed of the subject was installed on the ceiling of the corridor leading to the kitchen. By analyzing the walking speed distribution of this subject and all other subjects, we observed that subjects were generally most active between the hours 11AM and 6PM. Level of activity, in this case, corresponds to the magnitude of the subject’s speed. Another observation was, for some subjects who had the line of sensors installed in the corridor leading to the kitchen, we were able to potentially identify their meal times. For the male subject at hand, we could identify three distinct peaks: one peak with a walking speed of 51 cm/s at 7:30AM which potentially corresponded to breakfast time, another peak with a walking speed of 55 cm/s at 1PM which potentially corresponded to lunch time, and a third peak with a walking speed of 55 cm/s at 8:30PM which potentially corresponded to dinner time. Interestingly, the subjects had the fastest walking speed at these times.

When subjects were suffering from MCI, their walking speed distributions underwent significant changes. For the same male subject, for example, Fig. 3 depicts his walking speed distribution when suffering from MCI. The subject’s walking speed distribution did not follow a clear pattern as before. The three peaks, that potentially indicated the times of the three main daily meals, were not as distinct anymore. In addition, events seemed to be delayed compared to when the subject was cognitively intact. For example, the first distinguishable peak, that potentially corresponded to breakfast time, occurred at 8:30AM instead of 7:30AM. Another observation was that many subjects did not experience a slowing in their walking speed when they were suffering from MCI, as was the case with the male subject under discussion.

In order to quantify the difference between the walking speed distributions for subjects when cognitively intact and when suffering from MCI, we used dynamic time warping (DTW), which is a technique that uses dynamic programming to optimally align two signals such as the cumulative distance measure between the aligned samples is minimized [10]. The higher the DTW cost the greater the difference between the two signals or walking speed

distributions. What is special about DTW is that it ignores time shifts and returns a similarity cost based on differences in the distributions' shapes and magnitudes, which is what we are mostly concerned about in this problem.

Fig. 4 shows the distribution of the DTW similarity cost between walking speed distributions pertaining to the different states of cognition using data pertaining to all 15 subjects. According to Fig. 4, an increasing trend in DTW similarity cost is evident as we move from cognitive intactness to MCI. The DTW similarity cost is largest between cognitive intactness and MCI, reaching a maximum DTW cost of 700. Accordingly, there seems to be a significant difference in the walking speed distributions of the majority of the subjects when cognitively intact and when suffering from MCI.

A. Detecting MCI

After demonstrating a significant difference in the walking speed distributions of the majority of the subjects when cognitively intact and when suffering from MCI, we were interested in exploring detecting MCI in older adults using changes in their walking speed distributions. We formulated a classification problem, composed of two classes: "cognitively normal" which consisted of the "CIN" distributions, and the "cognitively abnormal" which consisted of the "MCI" distributions.

For each subject, we used all the "CIN" data to estimate a walking speed distribution, which served as the reference distribution as depicted in Fig. 5. Then a sliding time frame of size ω weeks, that scanned the entire speed data, was used to estimate walking speed distributions using a subset of the data. Each of the distributions estimated was compared to the reference distribution by computing the DTW similarity cost between the reference distribution and the distribution estimated using the time frame. The result was a trajectory of DTW similarity costs for each subject. The hypothesis was that the DTW cost would start increasing as the time frame would start sliding over the "TR" and the "MCI" data. As Fig. 5 shows, each distribution estimated using the time frame of ω weeks was labeled, where '-1' represented cognitive intactness, '0' represented transitioning, and '1' represented suffering from MCI.

By thresholding the resulting trajectories of the DTW costs, we generated two curves: the ROC curve by plotting sensitivity versus (1 - specificity) and the precision-recall curve by plotting precision versus recall. A DTW cost that was below the threshold was classified as "cognitively normal" and a DTW cost that was above the threshold was classified as "cognitively abnormal". The area under the ROC curve was denoted as AUC_{SS} , and the area under the precision-recall curve was denoted as AUC_{PR} . Table I presents a summary of the areas under the curves obtained using $\omega = 8$ weeks and $\omega = 12$ weeks.

Our approach significantly outperformed the approach described in our previous work using predefined measures associated with walking speed [6]. In [6], using a sliding window of size $\omega = 12$ weeks, we achieved AUC_{SS} and AUC_{PR} of 0.85 and 0.54, respectively. On the other hand, using the proposed approach and with a simple thresholding evaluation, we achieved AUC_{SS} and AUC_{PR} of 0.91 and 0.79, respectively, which means that we improved AUC_{SS} by 5.6% and AUC_{PR} by 25%.

V. CONCLUSIONS

In conclusion, we presented a novel approach of building walking speed distributions, which we demonstrated would potentially generalize better to new subjects. One direction for future work is to investigate this method further by devising a way to automatically detect MCI in older adults using changes in their walking speed distributions. This entails determining the sliding time window size that would yield the best results.

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Fig. 1.

Example of a subject who scored 0.5 on CDR scale on the 2nd year assessment onward [9].

Fig. 2.

Walking speed distribution estimated for a subject living in a one-bedroom apartment with sensors measuring walking speed installed in a corridor leading into the kitchen.

Fig. 3.

Walking speed distribution estimated for the same subject living in the one-bedroom apartment when suffering from MCI.

Fig. 4. Distributions of dynamic time warping similarity cost between a) cognitive intactness and transitioning walking speed distributions, b) cognitive intactness and MCI walking speed distributions.

Fig. 5.

Estimating reference distribution using “CIN” speed data, and estimating distributions using a sliding time window of size ω weeks.

TABLE I

Areas under curves generated by thresholding DTW costs.

Area Under Curve	Window Size (ω)	
	8 weeks	12 weeks
AUC_{SS}	0.850	0.906
AUC_{PR}	0.739	0.790