Scoring Cognitive Change Through Sensing and Analysis of Changing Driving Ability

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***Abstract*— This paper presents a scoring mechanism for the detection of cognitive change in individuals by sensing a high cognition task (driving). The paper identifies scoring algorithms that identify the variations in trips expected within subjects coping with cognitive decline. Trips are compared to a baseline performance set of attributes for the individual and also to gold standard performance (Google routing). Scoring tools are provided to identify subjects that are showing reduced ability or typical compensation techniques. Scoring identifies reduced trip complexity in either number of stops or trip distance and reduced ability to effectively navigate. A scoring tool is also provided to identify drivers experiencing difficulty operating the vehicle safely as indicated by reduced turn signal use. The result is a set of tools that allow a drivers performance to be tracked over time, identifying performance changes for a subject and need for interventions.**

Keywords- Cognitive Measurement, Cognitive Decline, Alzheimer Disease

I. INTRODUCTION

Small changes in cognitive ability are expected with aging but an increasing number of adults are developing functional impairments related to loss of cognition, called dementia. The most frequent cause of dementia is Alzheimer's disease and in Canada, the number of adults with dementia is expected to grow from 250,000 (1994) to 592,000 (2021) [1]. Early detection of dementia requires the measurement of cognitive change which can be difficult because of variance in the test results caused by many factors including appointment infrequency, variable patient tiredness, or time of day or focus as reported by Jimison [2], Morris [3], and Ritchie [4]. It has been shown by Peterson [5] and Doraiswamy [6] that early intervention is critical to achieve optimal outcome for dementia patients.

Ability to drive is one of the concerns for patients with cognitive decline. The clinical cognitive test used to measure impairment is a proxy for actual formal driving tests that are difficult to arrange and costly. An alternative is ongoing direct measurement of the performance of activities of daily living, providing direct evidence of the patient's ability or impairments. Measurement of computer game performance and web browsing has been proposed by Hagler [7] and Jimison [8] as measures of cognitive change. Sensor based systems to measure the physical well being of the subject and to detect changes in activity levels have been proposed by Hayes [9], Arcelus [10] and Taylor [11]. Sobolewski [12] reported on smart apartments for patient safety.

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High levels of social engagement and activities have been reported by Seeman [13] and Zunzunegui [14] to slow the progression of cognitive decline. The ability to drive can be an important component to maintain social engagements, especially for patients living in rural areas, while driving itself is an activity that requires high levels of cognitive function to be able to perform tasks such as trip planning and navigation. Anstey [15] and Marottoli [16] surveyed the driving habits of subjects with cognitive decline and showed that they adapt their driving habits to accommodate cognitive decline by reducing the quantity and variety of destinations. The use of familiar routes was shown by De Raedt [17] and Dubinsky [18]. Edwards [19] showed poorer health for older adults that stop driving as this resulted in a significant reduction in social engagements and activities.

Many trips associated with instrumental activities of daily living include the same destinations (shops, friends, social clubs or family) allowing trips to be measured and compared over time. Trends in performance changes could provide an indication of cognitive change. This paper proposes a scoring method for trips that have been analyzed for trip planning, navigation and driving tasks (turn signal usage) to distinguish variations that are indicative of cognitive change. This work uses healthy subjects to develop and validate the algorithms and techniques. Subsequent work will then use the algorithms with a larger group of subjects.

II. METHOD

The measurement of driving for individuals at risk or suffering from cognitive decline provides information that could provide an indication of cognitive function and change. The widespread and cost effective availability of GPS technology provides a mechanism to measure and record vehicle movements. A smart phone (iPhone 4GS running a GPS tracking application [20]) provides real-time GPS information (time, latitude, longitude, velocity, bearing, altitude) for the vehicle. Location is sampled every 5 seconds when vehicle velocity is greater than 20km/h, every 30 seconds if velocity less than 20km/h and every 60 seconds if vehicle is stopped, the slower sampling reduces wireless data network utilization when higher sampling provides no additional benefit because of low speed. Data is collected without the driver interacting with the device or reporting locations through other methods.

Video of the dashboard provides a record of the use of turn signals through the dashboard signal lamps. This paper reports on data collected from research test subjects (two of the authors) that were asked to drive to a series of familiar locations across a number of days. These trips included efficient although not necessarily optimal routes that can be used to establish the baseline performance and various inefficient routes (such as backtracking to home location) to demonstrate various coping mechanisms.

The collected data is analyzed through a series of steps:

1. Trip planning and navigational attributes analyzed from the GPS data - Wallace [21]:
   - Stops (destinations) are identified in the trip.
   - As-driven travel distance for trip.
   - Gold standard (Google) distances for as-driven stop order for overall trip and intra-stop segments.
   - Gold standard (Google) optimal travel distance and optimal stop order is determined.
2. Turns and signal usage analyzed:
   - Vehicle turns identified from the GPS data.
   - Turn signal use detected on dashboard videos.
3. Establish baseline: A set of trips are identified and combined to create a baseline performance.
   - Number of stops
   - Mean and standard deviation for:
     As-driven distances
     Google as-driven distance
     Google optimal distance
     As-driven segments / Google segments
     Signal usage performance

The performance on a specific trip is measured through a series of scores. The scoring model uses positive values to indicate poorer performance than baseline reference with zero representing similar to baseline performance. Since baseline reference is based on the individual's preferred route and not the Google optimal route, negative results indicating better than baseline are possible. Scores are assigned such that a significantly poorer performance from baseline is assigned a score of 2, while a minor change assigned a score of 1.

4. Trip complexity performance scores:
   - Newstops – represents stops on trip under analysis that are not in baseline trip
   - BaseStopsMissed – represents baseline trip stops that were not on this trip.
   - Change in trip complexity is derived from number of destinations on the trip compared to baseline:

$$Stp\_chg = (BaseStopsMissed - Newstops) \quad (1)$$

   - Together, these three measures give a view of the overall change in trip complexity.
   - The overall distance for a trip provides a measure of trip complexity shorter trips may be a coping mechanism. Trip distance is scored as follows:
     - Overall trip distance is compared to baseline:

$$DistancePerf = \frac{TripDistance - BaselineTripDistance}{BaselineTripDistance} \quad (2)$$

     - Scoring established:

$$\begin{gathered} DistancePerf > 0.1 \rightarrow Score - 2 \\ elseif > 0.05 \rightarrow Score - 1 \\ elseif > -0.05 \rightarrow Score\ 0 \\ elseif > -0.1 \rightarrow Score\ 1 \\ else \rightarrow Score\ 2 \end{gathered} \quad (3)$$

     - Positive score indicates driver has reduced the trip distance relative to baseline driving.
5. Segment level navigational performance provides a measure of the driver's ability to navigate efficiently between two locations and is scored as follows.
   - As-driven segment distances for trip compared to Google predicted distances for each segment:

$$SegmentResult = Mean\left(\frac{As - Driven\ distance}{Google\ Distance}\right) \quad (4)$$

   - Performance calculated by comparing with driver performance from the baseline trips.

$$SegPerformance = \frac{SegmentResult - BaselineSegmentPerformance}{BaselineSegmentPerformance} \quad (5)$$

   - Scoring established as:

$$\begin{gathered} SegPerformance > 0.1 \rightarrow Score\ 2 \\ elseif > 0.02 \rightarrow Score\ 1 \\ elseif > -0.02 \rightarrow Score\ 0 \\ elseif > -0.1 \rightarrow Score - 1 \\ else \rightarrow Score - 2 \end{gathered} \quad (6)$$

   - Positive score shows poorer navigational ability.
6. The trip level navigational performance has two scores, relative to Google predicted as-driven route and relative to Google optimal route:
   - Overall trip distance is calculated and compared to the baseline trip overall distance:

$$GoogleADPerf = \frac{TripDistance - GoogleADDistance}{GoogleADDistance} \quad (7)$$

$$GoogleOptPerf = \frac{TripDistance - GoogleOptDistance}{GoogleOptDistance} \quad (8)$$

   - Scoring established as:

$$\begin{gathered} Performance > 0.2 \rightarrow Score - 2 \\ elseif > 0.05 \rightarrow Score - 1 \\ elseif > -0.05 \rightarrow Score\ 0 \\ elseif > -0.2 \rightarrow Score\ 1 \\ else \rightarrow Score\ 2 \end{gathered} \quad (9)$$

   - Positive scores for Google as-driven indicate poorer navigational performance at the trip level while the Google optimal trip scores inefficient trip planning as well as poor navigational performance.

7. Turn signal utilization performance scoring:
   - Driver turn signal utilization is measured for each baseline trip leading to a percentage of turns (right, left and combined) signaled.
   - Baseline trips provide summary mean and standard deviation for turns signaled.
   - Signal utilization performance measured as:

$$PerformanceDelta = \frac{TripTurnsSignaled - BaseMeanTurnsSignaled}{BaseStDevTurnsSignaled} \quad (10)$$

   - Scoring established as:

$$\begin{gathered} PerformanceDelta > 3 \rightarrow Score - 2 \\ elseif > 1.5 \rightarrow Score - 1 \\ elseif > -1.5 \rightarrow Score\ 0 \\ elseif > -3 \rightarrow Score\ 1 \\ else \rightarrow Score\ 2 \end{gathered} \quad (11)$$

   - Positive scores indicate poorer signal utilization.

III. EXPERIMENTAL RESULTS

This research problem includes 4 major steps:

1. Analysis of the GPS data for each trip to determine key features such as stops and turns and navigational performance Wallace [21, 22].
2. Analysis of the video data for each trip to identify turn signals.
3. Fusion analysis of the video signal results with the GPS turn identification to identify turn signal usage.
4. Scoring the trip analysis data to provide an indication of the driver's performance.

Table 1 summarizes the trip data gathered for this work. A trip consisting of 6 baseline destinations (including start point) was used and it was repeated 8 times along with two additional trips that used the same home location and were of similar length to the baseline trip but used a new set of destinations. The trips were designed to provide a set of typical trips that included repeated trips, expected variations in those trips either by driver choice and lastly examples of typical variations related to cognitive decline. An example trace is shown in Figure 1 for Trip 1. The training trips included travel in both a clockwise and counter clockwise path. The trips included common variations that would be expected such as the addition or skipping of a stop, trips to differing sets of locations, trips with navigational errors or compensation mechanisms.

Figures 1 and 2 show two example route traces for trips 1 and 10 respectively with trip 1 having 5 stops in addition to the starting location that is shown in red. The route for trip 10 shares the same start location and one stop near the start, the balance of the stops are all unique to trip 9 and 10.

Table 2 shows the scoring results for the analysis of all the trips. One key compensation mechanism for drivers with cognitive decline is the reduction is trip complexity and this is shown in the first three lines of the scoring. The top two lines provide measure of the variation of a given trip from the baseline trip as the addition of new stops represents an increase in trip complexity whereas a reduction in stops represents a decrease in complexity and resulting cognitive challenge within the trip. The third line summarizes the trip complexity change for all the trips as minimal even though there was variation in the stops, at most the trips had 1 more or less stop than baseline.

Trip	Use	Attributes	Driver
1	Training	Baseline 6 stops, clockwise	Driver1
2	Training	Baseline 6 stops, clockwise	Driver1
3	Training	Baseline 6 stops, counter-clockwise	Driver1
4	Test	Baseline 6 stops, clockwise	Driver2
5	Test	Baseline 6 stops, clockwise, backtracking to home	Driver1
6	Test	Baseline 6 stops, counter-clockwise, small routing error	Driver2
7	Test	Baseline 6 stops + extra stop, counter-clockwise, poor signal utilization	Driver2
8	Test	Baseline 5 stops, counter-clockwise, stop 4 skipped	Driver2
9	Test	Baseline 1 stop + 4 extra stops, poor navigation decisions	Driver1
10	Test	Same as trip 9 but with good navigation and poor signal utilization	Driver1

Table 1: Summary of the driving trips captured

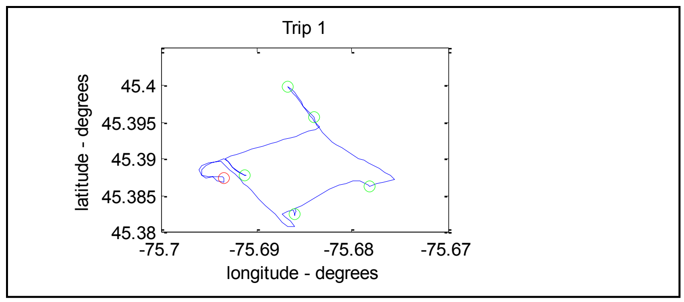

Figure 1: Trip trace for training Trip1 showing travel path and stops. Home location (trip origin) shown in Red and all other stops shown in Green.

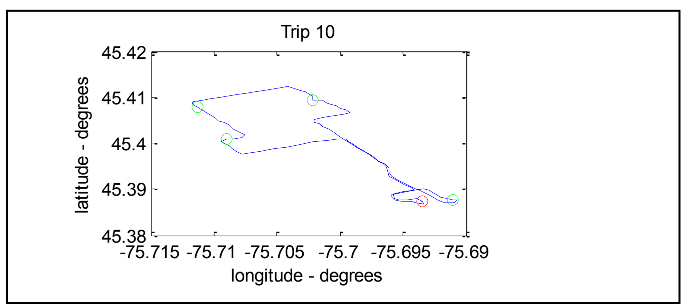

Figure 2: Trip trace for Trip10 showing travel path and stops. Home location (trip origin) shown in Red and all other stops shown in Green.

The fourth line of Table 2 provides a measure of the intra-stop navigational performance of the driver and it shows that the two trips (5 and 9) that included navigational issues are clearly identified. Trip 5 used backtracking to home whereas trip 9 included a wrong turn error. This scoring allows for trends in these of errors to be identified as a possible indication of cognitive change.

The trip level distance score provides another measure for overall trip complexity as drivers may compensate by choosing to stay closer to home. This scoring system was able to identify trip 8 that was missing a stop as lower complexity while the comparisons of the trip distance to Google as-driven and optimal routing provides measures of trips variation causes. For example, trips 5 and 9 although longer, are identified correctly as caused by poor navigational decisions whereas trip 7 and 8 are shown to have slightly better navigational performance to baseline.

Attribute \ Trip	Training 1	Training 2	Training 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9	Test 10
Number of baseline stops missed	0	0	0	0	0	0	0	1	4	4
Count of non baseline stops	0	0	0	0	0	0	1	0	3	3
Stop variation score	0	0	0	0	0	0	-1	1	1	1
Segment Performance Score	0	0	0	-1	2	0	-1	-1	2	1
Trip Distance Score	0	0	0	0	-2	-1	-2	2	-2	-2
As-driven Distance Performance score	0	0	0	-1	2	0	-1	-1	1	0
Optimal Distance Performance score	0	0	0	0	2	1	-1	-1	1	0
Right Signal use score	0	0	0	0	-1	1	0	0	-1	2
Left Signal use score	-1	-1	0	0	1	0	0	-2	0	2
Combine signal score	-1	0	0	0	0	0	0	-1	0	2

Table 2: Scoring summary for trips. Positive results (red) indicate poorer performance than baseline reference; Negative results (green) indicate improved performance over baseline reference.

Turn signal utilization scores are shown in Table 2 and the scoring system is able to identify trip 10 which was specifically driven with reduced use of turn signals.

IV. SUMMARY

This works demonstrates a potential scoring system for navigational, trip planning and turn signal analysis that can identify typical cognitive decline effects or compensation techniques including trip complexity reduction through stop reduction of distance reduction, reduced turn signal utilization and reduced navigational performance as compared to a drivers baseline performance and also Google gold reference. Each of the scores provides a separate measure of driving behaviors that may indicate cognitive change. A decline trend in any of the individual scores could be an indication of cognitive decline. The ongoing monitoring of driving behavior could provide information to caregivers on patient capability that augments clinical test information and mitigates variability issues.

The ongoing monitoring and scoring of a high cognition task such as driving provides information on change (or lack of change) in a patient's ability that can be provided to care givers such as family, physicians and the patient themselves. The information could give them either re-assurance that their abilities are not changing or be an indication of change enabling care givers to make interventions to assist patients, either by attempting to slow cognitive decline, or to ensure the ongoing safety and well being of the patient.

REFERENCES

[1] "Canadian Study of Health and Aging Working Group. Canadian Study of Health and Aging: Study methods and prevalence of dementia." *Canadian Medical Association Journal*, vol. 150, pp. 899-913, 1994.

[2] H. Jimison, M. Pavel, K. Wild, P. Bissell, J. McKanna, D. Blaker, D. Williams, "A Neural Informatics Approach to Cognitive Assessment and Monitoring," *Neural Engineering, 2007. CNE '07. 3rd International IEEE/EMBS Conference on* , pp.696-699, 2007.

[3] M. Morris, D. Evans, L. Hebert, J. Bienias, "Methodological Issues in the Study of Cognitive Decline", *Am. J. Epi.*, vol. 149 no. 9, pp. 789-793, 1999.

[4] K. Ritchie, S. Artero, J. Touchon, "Classification criteria for mild cognitive impairment: A population-based validation study", *Neurology* vol. 56, no. January, pp. 37-42, 2001.

[5] R. Petersen, J. Stevens, M. Ganguli, E. Tangalos, J. Cummings, S. DeKosky, "Practice parameter: Early detection of dementia: Mild cognitive impairment (an evidence-based review): Report of the Quality Standards Subcommittee of the American Academy of Neurology", *Neurology*, vol. 56, pp. 1133-1142, 2001.

[6] P. Doraiswamy, L. Kaiser, F. Bieber, R. Garman, "The Alzheimer's Disease Assessment Scale: Evaluation of Psychometric Properties and Patterns of Cognitive Decline in Multicenter Clinical Trials of Mild to Moderate Alzheimer's Disease", *Alzheimer Disease & Associated Disorders*, vol. 15, no. 4, pp. 174-184, 2001.

[7] S. Hagler, H. Jimison, M. Pavel, "Unobtrusive in-home assessment by means of everyday computer mouse usage," *Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE* , pp.3816-3819, 2011

[8] H. Jimison, M. Pavel, T. Le, "Home-based cognitive monitoring using embedded measures of verbal fluency in a computer word game," *Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE* , pp.3312-3315, 2008

[9] T. Hayes, S. Hagler, D. Austin, J. Kaye, M. Pavel, "Unobtrusive assessment of walking speed in the home using inexpensive PIR sensors," Engineering in Medicine and Biology Society, 2009. EMBC 2009. *Annual Int. Conference of the IEEE* , pp.7248-7251, 2009.

[10] A. Arcelus, I. Veledar, R. Goubran, F. Knoefel , "Measurements of Sit to-Stand Timing and Symmetry from Bed Pressure Sensors", *IEEE Trans. on Inst. and Measurement*, vol. 60, no. 5, pp. 1732-40, 2011.

[11] M. Taylor, D. McEwen, R. Goubran, H. Finestone, F. Knoefel , "Assessing Standing Stability of Older Adults using Pressure Sensitive Arrays", *Proc. of IEEE International Workshop on Medical Measurements and Applications*, Budapest, Hungary, pp.1-5, 2012.

[12] R. Sobolewski, R. Reilly, S. Finnigan, P. Dockree, K. O'Sullivan, I. Robertson, "Monitoring of cognitive processes in older persons," *Neural Engineering, 2009. NER '09. 4th International IEEE/EMBS Conference on* , pp.132-135, 2009.

[13] T Seeman, D. Miller-Martinez, S. Stein Merkin, M. Lachman, P. Tun, A. Karlamangla, "Histories of social engagement and adult cognition: midlife in the U.S. study",) *J Gerontol B Psychol Sci Soc Sci*, vol. 66 suppl 1, pp. i141-52, 2011.

[14] M. Zunzunegui, B. Alvarado, T. Del Ser, A. Otero, "A Social networks, social integration, and social engagement determine cognitive decline in community-dwelling Spanish older adults", *J Gerontol B Psychol Sci Soc Sci*, vol. 58, no. 2, pp. S93-S100, 2003.

[15] K. Anstey, J. Wood, S. Lord, J. Walker, "Cognitive, sensory and physical factors enabling driving safety in older adults", *Clinical Psychology Review*, Vol 25, no. 1, pp. 45-65, 2005.

[16] R. Marottoli, C. Mendes de Leon, T. Glass, C. Williams, L. Cooney, Jr., L. Berkman, "Consequences of Driving Cessation: Decreased Out-of-Home Activity Levels", *J Ger. B Psychol Sci Soc Sci*, vol. 55, no. 6, pp. S334-S340, 2000.

[17] R. De Raedt, I. Ponjaert-Kristoffersen, "Can strategic and tactical compensation reduce crash risk in older drivers?", *Age Ageing*, vol. 29, no. 6 pp. 517-521, 2000.

[18] R. Dubinsky, A. Stein, K. Lyons, "Risk of driving and Alzheimer's disease (an evidence-based review): Report of the Quality Standards Subcommittee of the American Academy of Neurology", *Neurology,* vol. 54, June, pp. 2205-2211, 2000.

[19] J. Edwards, M. Lunsman, M. Perkins, G. Rebok, D. Roth, "Driving cessation and health trajectories in older adults", *J Gerontol A Biol Sci Med Sci*, vol. 64, no. 12, pp. 1290-1295, 2009.

[20] www.instamapper.com

[21] R. Wallace, R. Goubran, F Knoefel, "Cognitive Change Measurement Through Driving Navigation Ability Sensing and Analysis", *MeMeA 2013*, 2012.

[22] R. Wallace, R. Goubran, F Knoefel, "Measurement of Driving Routes and Correlation to Optimal Navigation Paths", *I2MTC* 2013, 2013.