Measurement of Signal Use and Vehicle Turns as Indication of Driver Cognition

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Abstract— **This paper uses data analytics to provide a method for the measurement of a key driving task, turn signal usage as a measure of an automatic over-learned cognitive function drivers. The paper augments previously reported more complex executive function cognition measures by proposing an algorithm that analyzes dashboard video to detect turn indicator use with 100% accuracy without any false positives. The paper proposes two algorithms that determine the actual turns made on a trip. The first through analysis of GPS location traces for the vehicle, locating 73% of the turns made with a very low false positive rate of 3%. A second algorithm uses GIS tools to retroactively create turn by turn directions. Fusion of GIS and GPS information raises performance to 77%. The paper presents the algorithm required to measure signal use for actual turns by realigning the 0.2Hz GPS data, 30fps video and GIS turn events. The result is a measure that can be tracked over time and changes in the driver's performance can result in alerts to the driver, caregivers or clinicians as indication of cognitive change. A lack of decline can also be shared as reassurance.**

Keywords— Cognitive Measurement, Cognitive Decline, Alzheimer Disease, Data Analytics

I. Introduction

The ongoing driving competence of older adults with cognitive decline and patients after medical illness or injury are two examples of driving groups where monitoring of their behaviors can lead to a better understanding of the risk in their continued driving and also identify the need for preventative measures. Medical professionals face challenges currently as they have to determine whether an individual should lose their license permanently or temporality based on their clinical assessment of the patients' abilities. Compliance of drivers that restrict driving voluntarily or due to restricted licenses can also be monitored. One cause of functional impairments and cognitive decline for aging adults is dementia. Its most frequent cause is Alzheimer's Disease and is expected to grow in Canada from 250,000 (1994) to 592,000 (2021) patients [1]. The ability and right to drive is important for these patients as it enables mobility for social engagements and activities as reported by Seeman [2] and Zunzunegui [3] that slow the progression of cognitive decline. Similarly, Edwards [4] showed patients that stop driving have poorer health as a result of reduced social engagements.

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Driving requires cognitive functions to be performed safely as it includes executive tasks such as navigation and trip planning through to the autonomous/trained responses associated with the details of vehicle operation. Eby [5,6] and Molnar [7] have studied the driving habits of subjects with cognitive decline and found that they frequently adapt their driving patterns, such as restricting distance traveled, reduced trip complexity or limiting the time of day. In many jurisdictions, physicians are required to advise licensing authorities if they have concerns about driving risk. At this time, they use indirect measures such as history, physical exam and cognitive tests to help determine driving risk. Cognitive change measurement is challenged by limited frequency of tests due to limited clinician availability and variability caused by patient tiredness, time of day or focus as reported by Jimison [8], Morris [9], and Ritchie [10]. Killane [11] reported on the linkage between cognition and measurements of a subject's gait, Kato [12] reported on cognitive impairment detection from speech prosody while Roy [13] reported on real time measurement of mental fatigue through EEG.

The measurement of executive cognitive function for navigation was reported by Wallace [14, 15]. Marshall [16, 17] and Eby [4] reported on studies of older drivers where the vehicles have been out-fitted with sensor technology providing additional insights into executive cognitive decisions such as trip frequency, duration, distance and time of day. Turn signal use is one of many cognitive functions associated with driving as drivers perform (or skip) based on their automatic actions through training and experience. Eye focus areas is another automatic/trained action and analysis to ensure the driver is focusing on the forward direction of travel, dashboard, mirrors and blind-spots for the appropriate amount of time and at the appropriate times.

Few driving studies report on the measurement of turn signal usage as it requires a source of both the turn indicators and the associated events requiring signals. Eby reported on the tracking of turn signal use through tail light electrical signals but the use of these signals required modification to the car electrical system and the events requiring signals were found through the use of a closed course or direct researcher observation. Another source of turn signal data is dashboard video of the turn signals indicator lamps available through the dashboard CANbus interface that uses proprietary protocols that vary between automobile makers.

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On Board Diagnostics II (OBDII) is a standard engine computer interface that does not include signal information.

II. METHOD

The measurement of turn signal use as an indication of autonomous cognition while driving requires sensors that allow both the detection of the turn indictors and the events requiring signaling. The chosen sensors consisted of dashboard video cameras of the signal lamps and a smart phone based GPS sensor. The latter sensor data was used to obtain as-driven GIS turn information from Google Maps. Through the application of data analytics techniques to these data sets, a measure of turn signal performance is proposed. The GPS location technology was previously reported [14, 15] and the dashboard video had to accommodate dashboards that had the turn signal lamps widely separated (two cameras) and those with closely placed lamps (one camera). CANbus was not chosen due to the proprietary protocols. Signal lamp voltage was also rejected to avoid potential impact to operation of the signals and the need for no permanent modification on the vehicle. Audio analysis for clicking sound is an alternative method to capture the signal use, but this would not allow signal direction to be determined. The Google Maps API was chosen as a GIS map source as it is widely and freely available and the API allows for automated algorithms to obtain turn location events.

A. Dashboard signal lamp detection

Identification of the turn indicator status is an example of a general image processing problem where the event being detected has known features (arrow shape in this case) but unknown size/scale, position, orientation (tilted or not coplanar with camera), noise (vibration) and the detectable feature (lamp lit) repeats indicating a longer duration event (signal engaged). The algorithm requires the analysis of the video to detect the lamp and the signal is on between the first detected "on" transition through to the last detected "off" transition. The algorithm must adapt to the location of the signal lamps on the dashboard, support variation in dashboard lamp placement (single video for both or separate videos), it needs to distinguish arrows from other signal lamps and determine the direction of the arrow. Grey scale video images represented by unsigned integers were used in the work and analysis was performed on forward and backward difference images and associated measures of the variance and energy in the delta images.

$$ForDelta = Image[n] - Image[n-5] \quad (1)$$
$$BackDelta = Image[n-5] - Image[n] \quad (2)$$
$$ForVar = Var\ (ForDelta) \quad (3)$$
$$BackVar = Var\ (BackDelta) \quad (4)$$
$$ForEnergy = \sum ForDelta^2 \quad (5)$$
$$BackEnergy = \sum BackDelta^2 \quad (6)$$

Regions in the image were identified by looking for localized areas of high energy in the delta images:

$$Turing\ on: \quad ForVar > 150 * ForEnergy \quad (8)$$
$$Turing\ off: BackVar > 150 * BackEnergy \quad (9)$$

The location of the lamp was observed to move either through vibration of by bumping causing a step move in position. A candidate window is chosen in region with highest energy. Given that the signals cannot be guaranteed to be horizontally aligned with the camera frame, the correlation is measured for the candidate arrow from -15^{o} to +15^{o} rotations in 1^{o} steps. At each rotation of the candidate arrow is cropped based on Matlab canny edge detection and the correlation of candidate arrow with ideal left and right arrows scaled to same size as candidate is measured. If maximum correlation of left vs. right is not at least 2% different, candidate is rejected as not an arrow removing lamps other than arrows. Turn signal state is then created by processing the lamp on-off states where the signal is on between the first lamp "on" detection to a lamp off detection that does not have a lamp on within 0.5 seconds.

B. Turn detection in GPS data

The GPS data is analyzed to locate vehicle turns. At each GPS location point, two vectors are formed; A for segment entering the location and B for segment leaving the location. To avoid noise from GPS jitter while stopped short segments are omitted. The magnitude of the direction change is determined from a dot product while cross product provides direction.

$$\text{angle} = cos^{-1}((A \cdot B)/(|A|\ |B|)) \quad (10)$$

$$\text{direction} = sign((A \times B)_{z\ component}) \quad (11)$$

Candidate corners are then identified as changes greater than 30^{o} which are then filtered to ensure higher velocity turns (ramps) only have the first of consecutive detections accepted.

C. GIS Turn by Turn route creation

Google Maps provides a GIS database accessible through APIs and previous work has shown these APIs can be used to analyze navigational performance. They can be used to find the location of turns and merges within a route retroactively. Each trip segment is represented by a start and stop location (longitude, latitude) and up to 8 (Google API limitation) intermediate locations that are equally spaced in time, resulting in a set of routing directions. The route query is repeated for 1 less intermediate point for a second measure as different points prevent the vehicle from being placed on the wrong road, for instance a small GPS measurement error near a bridge leading placement on the wrong road.

The XML file returned by Google Maps Directions API includes turn by turn directions for the trip along with trip summary information. The trip distance estimate for the two sets of directions is compared to the actual as-driven distance and the result closest to actual driven distance is chosen. The XML turn and merge events set (longitude, latitude, direction (left/right) and type (turn/merge)) from the directions is a series that has known order of occurrence and known location while the GPS trip data is a time series of longitude and latitude samples. The turn events need to be time aligned to the actual as driven location samples through a minimum distance error measure for the as-driven samples to the turn events. A tree search is used to find the ordered as-driven locations that provide the minimum total distance error for the turn events.

$$Error\ Distance = \sum_{k=1}^{n} |Distance\ errors| \quad (12)$$

D. Correlation of GPS and GIS turns with dashboard video

The now time aligned GPS data and GIS identified turns must be sampling rate aligned with lamp events and this is an example of a general sampling rate transformation problem where data is not only at highly differing sampling rates but in the case of GPS data, the sampling rate is variable and the key features of the higher sampling rate must be maintained (signal events) as it is down sampled.

The video events are down sampled to align with GPS/GIS information where each new sample reflects the state of the turn signal lamps in preceding interval (left, right or off). GPS and GIS turns data and lamp status information is then compared resulting in three vectors for each:

- Signal events associated with turns
- Signal events not associated with turns
- Turns with no associated signals.

III. EXPERIMENTAL RESULTS

Data was collected for a total of ten trips driven by two different healthy drivers [14,15] where each driver drove their personal vehicle. The drivers were both male, ages 48 (Driver 1) and 51 (Driver 2). The two vehicles had different dashboard configurations with one having adjacent turn signal lamps (driver 2) allowing one camera to capture both signals while the other (driver 1) required separate cameras for each signal.

Video capture of the dashboard proved challenging as car designs include shade structures to prevent sunlight from getting onto the dash in addition to the steering wheel blocking many camera positions. Only 2 locations were found to give an acceptable image of the turn signals. Mounting near the driver's head which was unsafe as it could interfere with driver head movements and vision. Hanging the cameras from the top of the dashboard between the steering wheel and dashboard was chosen. The cameras used were extremely small in size (66mm x 29mm x 15mm) so they minimally obscured the dashboard and the driver could easily see around them as needed. This mounting location caused the cameras to be mounted upside down requiring all analysis to account for the image inversion.

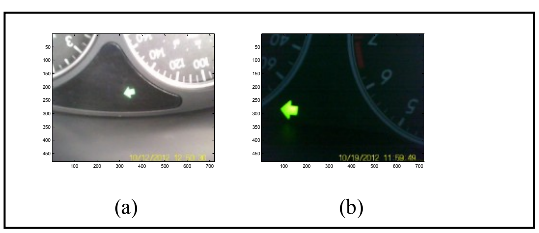

Figure 1: Example right turn lamp image: (a) vehicle 1; (b) vehicle 2.

An example dashboard image is shown in Figure 1 for each of the vehicles. The video included a time stamp that was used for alignment of the video and GPS data. The lower band of the image that included the timestamp was excluded from all image analysis. The turn signal events captured on video include 225 separate uses of the signals that were almost evenly split between left and right (118 right, 107 left). The turn signal events ranged from a single flash of the lamp through to events of over 100 flashes. The performance of the detection algorithm is shown in Table 1. It detected 100% of the signal events with no missed detections and produced no false positive detections. The algorithm proved to be robust to the effects of vibration from car motion or incidental bumps of the camera.

Table 1: Summary of results for signal arrow detection showing all turn signal events were detected with no false positive or false negative errors.

Signal	**Detected**	**False Positive**	**False Negative**
Right signal (n=118)	100%	0%	0%
Left signal (n=107)	100%	0%	0%
Combined (n=225)	100%	0%	0%

The addition of rotation to the algorithm was key to achieve the performance. Examples of the steps are shown in Figure 2 as the shape of car dashboards and camera mounting position prevents co-planar and horizontal alignment. The candidate arrows are incrementally rotated before correlation to determine the optimal result. The image detection using grey-scale isolated the algorithm from variation in dashboard lamp colour. To be able to easily identify both the on and off transitions of the lamps, it was determined that analysis of a delta image provided the best reference. The delta image excluded most of the background other than vibration effects so that only lamp transitions remained. A 5 frame delta was found to ensure that at least 2 deltas were calculated between full on and full off for each lamp flash as the lamps needed time to change state.

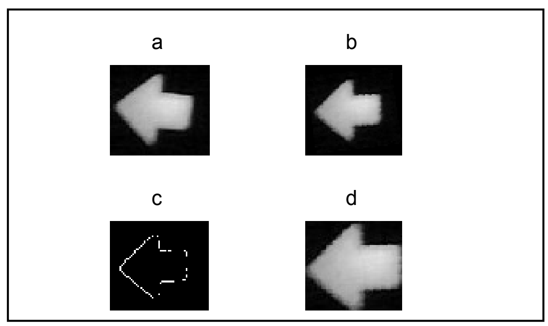

Figure 2: Example of arrow detection algorithm image processing steps.
a – Difference image for raw window containing potential signal arrow.
b – Candidate image rotated to position with optimal correlation.
c – Edge detection results for rotated candidate arrow.
d – Cropped candidate arrow used for correlation.

The results of the GPS analysis and Google based GIS remapping are summarized in Table 2. Of the 215 turns taken, 73% of them were correctly detected by the GPS turn detection algorithm while only 58% were detected by the Google GIS algorithm. A key difference in the two algorithms is that the Google GIS algorithm performed well locating turn and merge events on the road network but failed within parking lots and in transitions from road to parking lots. The GPS algorithm was able to locate non-road events but missed merges and some turns into/out of parking lots where parking was directly beside the road, with minimal travel distance pre/post turn.

The false positive detection rate on roads is relatively low at 2 - 6% for identified corners that are not actual corners. Most of these detections are associated with long curved segments of a road where traffic causes the driver to slow. The extra false positive errors for the Google data are mostly associated with two segments where there was a drop out in the GPS data so an alternative path for a portion of the segment was returned by the API.

Table 2: Summary performance for the GPS and GIS remapping algorithms in the detection of turn and merge events within the trips.

Turns	GPS only	Google only
Right turns (n=131)		
Detected turns	73%	62%
False Positive errors	3%	5%
False Negative errors	14%	23%
Left turns (n=86)		
Detected turns	72%	55%
False Positive errors	2%	6%
False Negative errors	15%	24%
Total (n=215)		
Detected turns	73%	58%
False Positive errors	3%	4%
False Negative errors	14%	21%

The correlation of the turn signal usage events identified in the video signals is shown in Table 3. On a standalone basis, the GPS algorithm performs better than the Google GIS algorithm. This is expected because of the Google algorithm does not identify non-road events. When the signal events for the two algorithms are combined, the performance improves.

Table 3: Resulting association of signal lamp use with identified turns.

Signalled Turns	GPS only	Google only	Combined
Right turns	81	74	89
Left turns	55	46	62
Total	136	120	151

Table 4: Turn signal usage rates for the two drivers.

Signalled Turns	Driver 1	Driver 2
Right turns	67%	70%
Left turns	68%	77%
Total	67%	73%

Table 4 shows the performance measures for the two drivers where Driver 2 demonstrates a higher tendency to signal turns than Driver 1 and provides a different measure of driving performance that can be can be combined with navigational performance [14, 15]. It is not expected that a driver will remember to use their signal at every turn but it is expected that a driver will have relatively consistent performance and any long term change in this performance could indicate cognitive change.

IV. SUMMARY

This work demonstrates that an automatic over-learned cognitive function associated with driving can also be measured adding to the more complex executive cognitive functions reported previously. This requires the use of a sensor fusion algorithm of GPS sensor information, GIS remapping and a sensor system using video capture and analysis of the dashboard videos for signal lamps use. The algorithm provides a measure of the driver's performance for use of turn signals for actual turns performed. The result is an algorithm that can analyze a given driver's performance over time as an indication of change in driver ability. Should the driver's performance show signs of decline, the system can provide the driver with feedback. The results can also be shared with the driver's caregivers and physicians providing a much more detailed view on the driver's performance or can be used to determine intervention plans as needed.

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