Naturalistic Driving Measures of Route Selection Associate With Resting State Networks in Older Adults

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Abstract

Within a cohort of cognitively normal older individuals, we compared performance on naturalistic driving with resting state functional connectivity using machine learning. Functional networks associated with the ability to interpret and respond to external sensory stimuli and the ability to multi-task were associated with measures of route selection. Maintenance of these networks may be important for continued preservation of driving abilities. It is possible that targeted interventions could be developed to train these networks.

Introduction

Driving requires the integration of a diverse set of skills, including planning, adjusting to novel external stimuli and responding to visual cues[1]. Older drivers have an increased risk of crashes that may be due to age-related changes in sensorimotor processing in combination with difficulties in spatial navigation[2,3]. The average older adult ceases driving about seven years prior to the end of their lives[4,5]. For individuals who stop driving, many will develop depression, lower social participation and physical activity, and increased risk of transition to institutional care [6]. Interventions that could enable older adults to continue driving could have important societal benefits.

Resting state (rsfc) functional MRI (fMRI) is an imaging technique that is highly sensitive to brain activity. It measures this activity indirectly by quantifying changes in blood flow that correspond with changes in neural activation. These observed blood oxygen level dependent (BOLD) changes map onto well-established networks that are also observed in a task-based paradigm[7,8].

A number of task-based fMRI studies have evaluated participants completing driving-related tasks using simulators[9–12]. A diverse set of networks, including attention, motor control, decision making, and the sensory networks have been shown to be activated. However, only one study has evaluated rsfc as a function of driving skill. The study compared taxi drivers (skilled drivers) and non-drivers, finding that taxi drivers possessed stronger connections integrating higher order control networks with sensory networks, and weaker connections between sensory networks[1].

Here we evaluated naturalistic driving data collected over a multi-year period for 64 cognitively normal older adults (ages 60 – 85) and applied machine learning to identify rsfc networks that associate with driving behaviors. This is an important addition to our understanding of the functional changes that associate with aging, as we are able to connect measurements corresponding to real world tasks (in this case, naturalistic driving data) with neuroimaging data.

Methods

Participants

Cognitively normal older adults (n=64) enrolled in a driving study affiliated with the Knight Alzheimer Disease Research Center (ADRC) at Washington University in St. Louis (WUSTL) were included in this analysis. Methods of recruitment have been previously described[13,14]. All participants undergo regular cognitive screening, and all participants also completed vision screening. This study was approved by the WUSTL Institutional Review Board and each participant provided signed informed consent. Research was performed in accordance with all relevant guidelines and regulations, including the Declaration of Helsinki Ethical Principles for Medical Research involving Human Subjects.

Imaging

We obtained both structural and functional MRI on a 3T Siemens biograph scanner (Erlangen, Germany). A detailed description of acquisition and processing can be found in the supplement. We used a seed-based approach for rsfc. After calculating the mean time series for each functional region of interest (ROI), we calculated the pairwise correlations between each ROI. Then we sorted these seeds into 13 pre-defined networks to develop a 13 x 13 matrix of inter- and intra-network connections[8]. All imaging data was collected within 2.5 years of driving study enrollment.

Driving

Naturalistic driving was captured using the Driving Real-World In-Vehicle Evaluation System (DRIVES)[13,14]. This data was obtained through the use of a GPS data logger (G2 Tracking Device, Azuga Inc, San Jose, CA), installed in the onboard diagnostics-II port of a vehicle. Date, time, speed, latitude and longitude coordinates at 30-second epochs were collected whenever a vehicle drove. In addition to the breadcrumb data, trip summary values including total distance travelled, counts of hard braking incidents, hard accelerations, and duration exceeding the speeding limit for each trip were collected. All participants supplied more than one year of driving data (= 3.01 years, = 1.06 years). Detailed information on participant enrollment duration and time between rsfc collection and driving study participation is available in the supplement.

Statistics

Driving parameters (complete list available in Table 1) were compressed into single values for each driver over their entire recorded driving history. We performed a 1000 bootstrap lasso regression with 10-fold cross-validation for lambda selection, using a previously described approach[15]. We applied the R package glmnet for implementation[16]. For each bootstrap iteration, we trained on 2/3 of the data and tested on the remaining 1/3. We took each of the driving parameters in turn as the response variable, and included each rsfc correlation value and driver age as features in the model. We looked for models with mean absolute percent error (MAPE) of less than 10% indicating good forecasting power. In order to identify the features that contributed the most to generating good predictions, we counted the number of times each feature was retained by lasso regression (see Figure 1).

Results And Discussion

After evaluating a variety of driving behavioral metrics, we found strong predictability for two measures (straightness and actual-optimal distance ratio) with regards to rsfc networks. We observed positive correlations between within-network ventral attention network (VAN x VAN) and salience – dorsal attention network (SAL x DAN) and straightness, as well as a positive correlation between frontoparietal – subcortical network (FP x SubCort) and the actual-optimal distance ratio in this sex-balanced cohort of cognitively normal older adults.

In animal movement literature, maximum route straightness (straightness = 1) is considered the most efficient orientation posture; however, even in the natural world animals frequently are not able to follow perfectly direct routes due to any number of obstacles posed by the physical environment or potential predators[17]. By extension, drivers are constrained by transportation infrastructures and it is thus unlikely that they are able to select perfectly straight routes. We considered higher straightness to represent more optimal route finding, even given environmental constraints. It is likely that low straightness values would indicate drivers who are getting lost more frequently and exhibiting avoidant driving behaviors that lead them to take longer and/or more circuitous routes, such as the route shown in Figure 2B. In Figure 2B we see a driver who took a much longer and circuitous route (shown in red) in order to avoid a highway (the optimal route, shown in black).

Median route straightness (Figure 2A) could be predicted with 6.4% MAPE. A strong VAN x VAN connection was associated with greater route straightness (Figure 2C, 2E). The VAN is responsible for bottom up attentional processing[18,19], specifically, for exercising control upon receipt of various extrasensory stimuli. The SAL x DAN inter-network connection also positively correlated with route straightness (Figure 2C, 2F). The SAL x DAN network has been shown to associate with motor inhibition[20]. Taken together, we see that the two most important networks used for predicting route straightness were associated with the ability to respond to a complex external environment, including the ability to alter pre-planned motor activities.

Despite the utility described above, we acknowledge that utilizing straightness as our primary route selection metric could be heavily influenced by the availability of roads. Therefore, we used OpenStreetMap to identify the theoretically optimal route, which optimizes routing by predicted travel duration, meaning that it finds the route that should be quickest rather than shortest distance[21]. Our working assumption was that drivers who take longer routes than the optimal route were either getting lost, choosing to drive in primarily familiar areas even if they were not the most direct path from point A to point B, or intentionally avoided challenging driving scenarios like high speed environments (again, see Figure 2B) or complex intersections. We were able to predict the median actual – optimal distance ratio with 2.0% MAPE.

We observed a positive correlation between our primary resting state network, this time FP x SubCort, and the driving metric in question (Figure 2D, 2G). Lower FP x SubCort values indicate a greater proficiency at multi-tasking[22]. Drivers who exhibited greater multi-tasking ability based on their rsfc values had lower actual-optimal distance ratios, suggesting that the ability to multi-task is important to the ability to consistently drive more direct routes. Notably, FP x SubCort changes occur with training[22], meaning that FP x SubCort targeted interventions could potentially lead to longer retention of access to personal vehicles for older adults.

We expected straightness and the actual-optimal distance ratio to contain similar information; however, they were relatively weakly correlated (R = 0.22). These results suggest that different information is conveyed by the straightness index and the actual-optimal distance ratio. Future work that investigates individual routes rather than aggregated median values is necessary to enhance our understanding of these differences. Both metrics seem to relate to wayfinding in a naturalistic driving setting; however, we are not able to determine if either (or both) are reflective of intentional route selections (e.g. drivers choosing to avoid complex driving scenarios) or errors in wayfinding. If these factors could be isolated, we could potentially derive even greater insight into the neurological underpinnings of different features of driving with aging.

We observed that for older adults, retention of strong networks associated with the ability to interpret and respond to external sensory stimuli and the ability to multi-task played important roles in the route selection process. This general pattern aligns with the observed result of stronger connections between control and sensory networks for drivers [1]. Defining these relationships is the first step to the development of targeted interventions like cognitive training. Longer retention of access to personal vehicles could increase the number of older adults that could age-in-place, as well as maintain the sense of autonomy that comes with the ability to independently navigate.

Declarations

Author Contributions

JKW – Project conception, data analysis, drafting of manuscript

CMR – Collection of driving data, revision of manuscript

GMB – Collection of driving data, revision of manuscript

NM – Collection and processing of MRI data

AMJ – Collection of driving data

SM – Collection of Driving Data

JH – Collection of Driving Data

JMD – Collection of Driving Data, revision of manuscript

JCM – Collection of all data

BMA – Supervision of project, revision of manuscript

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DISCLOSURES:

Julie K. Wisch reports no disclosures.

Catherine M. Roe reports no disclosures.

Ganesh M. Babulal reports no disclosures.

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Tables

Table 1
Participant Demographic Data

	Participants **(N = 64)**
Age at MRI (Years)	
Mean (SD)	71.3 (5.06)
Median [Min, Max]	70.3 [60.0, 84.7]
Sex	
Male	32 (50%)
Female	32 (50%)
Education (Years)	
Mean (SD)	16.6 (2.19)
Median [Min, Max]	16.0 [12.0, 20.0]
Time from Start of Driving Enrollment to MRI (Years)	
Mean (SD)	0.997 (1.01)
Median [Min, Max]	1.03 [-2.00, 2.49]
Time from End of Driving Enrollment to MRI (Years)	
Mean (SD)	4.01 (1.03)
Median [Min, Max]	3.91 [1.69, 6.55]
Radius of Gyration (mi)	
Mean (SD)	257.4 (251.4)
Median [Min, Max]	177.6 [18.54, 1146]
Median Distance Travelled (mi)	
Mean (SD)	4.12 (2.40)
Median [Min, Max]	3.29 [0.684, 14.3]
Median Route Straightness	
Mean (SD)	0.718 (0.0535)
Median [Min, Max]	0.725 [0.589, 0.838]
Median Actual-Optimal Distance Ratio	
Mean (SD)	1.00 (0.0266)

	Participants **(N = 64)**
Median [Min, Max]	0.999 [0.939, 1.10]
Median Actual-Optimal Time Ratio	
Mean (SD)	1.32 (0.274)
Median [Min, Max]	1.25 [0.940, 2.15]
Number of Trips per Year	
Mean (SD)	619 (360)
Median [Min, Max]	565 [120, 1950]
Mean number of hard braking events per trip	
Mean (SD)	0.110 (0.0882)
Median [Min, Max]	0.0931 [4.80e-03, 0.509]
Mean number of hard acceleration events per trip	
Mean (SD)	0.0423 (0.101)
Median [Min, Max]	0.0127 [0, 0.746]
Mean number of overspeeding events per trip	
Mean (SD)	0.394 (0.422)
Median [Min, Max]	0.288 [0, 1.94]
Mean percentage of trip time sepnt overspeeding	
Mean (SD)	0.0122 (0.0168)
Median [Min, Max]	6.76e-03 [0, 0.0845]
Mean number of unique destinations per year	
Mean (SD)	201 (103)
Median [Min, Max]	187 [50.5, 520]
Ratio of unique destinations to total destinations	
Mean (SD)	0.341 (0.0811)
Median [Min, Max]	0.335 [0.208, 0.530]

Figures

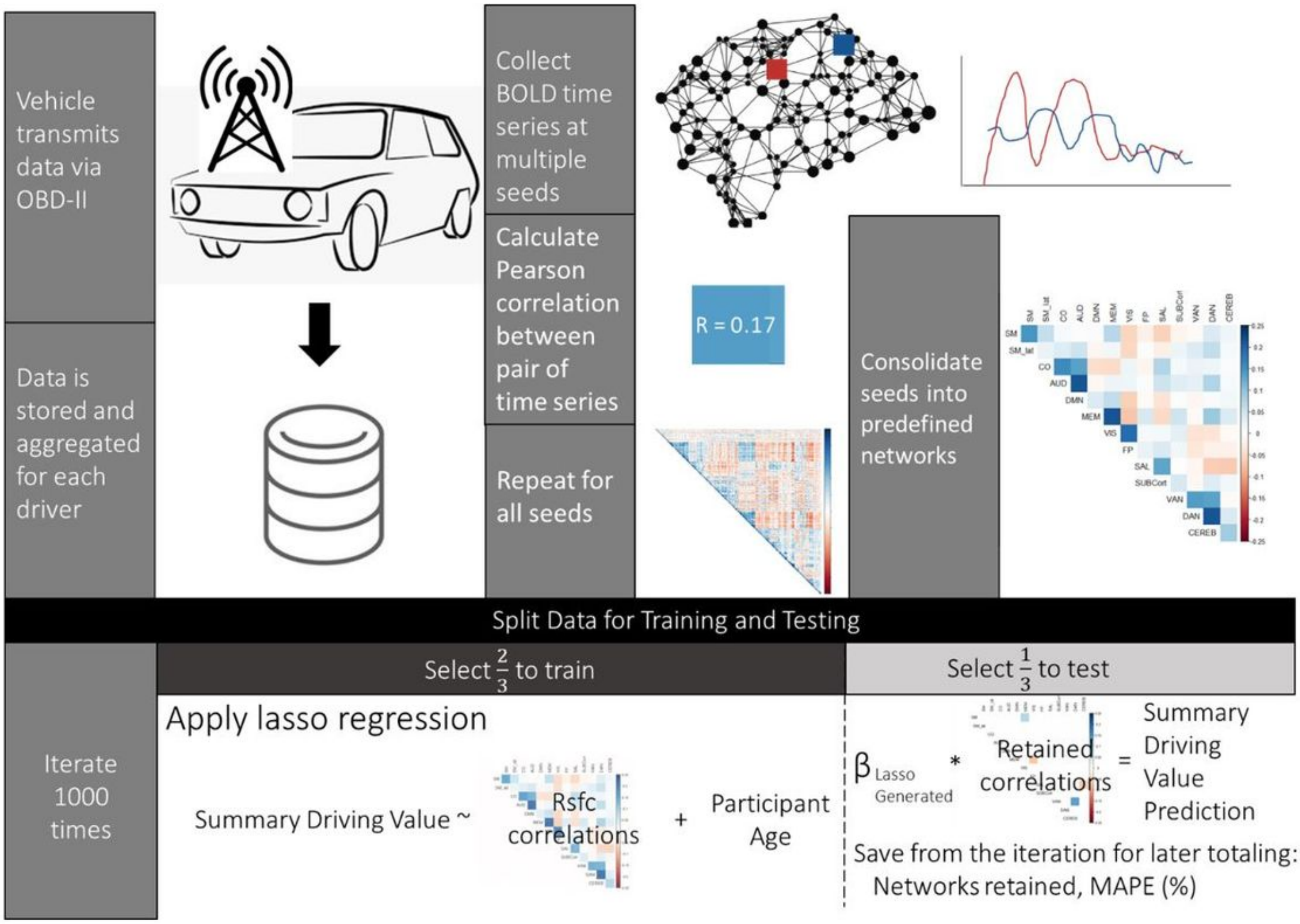

Figure 1

Vehicle data was collected via chip transmission (OBD-II), and single summary values were created for each measurement on a driver-by-driver basis. Resting state functional connectivity (rsfc) functional magnetic resonance imaging (fMRI) was collected with time series data converted to a matrix of correlations, consistent with previously published methodology. We then used a 1000 bootstrap procedure to identify rsfc networks that predicted driving performance variables. For each iteration, we trained the model on two-thirds of the dataset and evaluated the model performance on the remaining one third. From each iteration we kept the networks that were retained by the lasso algorithm and the mean average percent error of the proposed model. At the conclusion of the 1000 iterations, we counted the total number of times each network was retained and calculated the total mean average percent error.

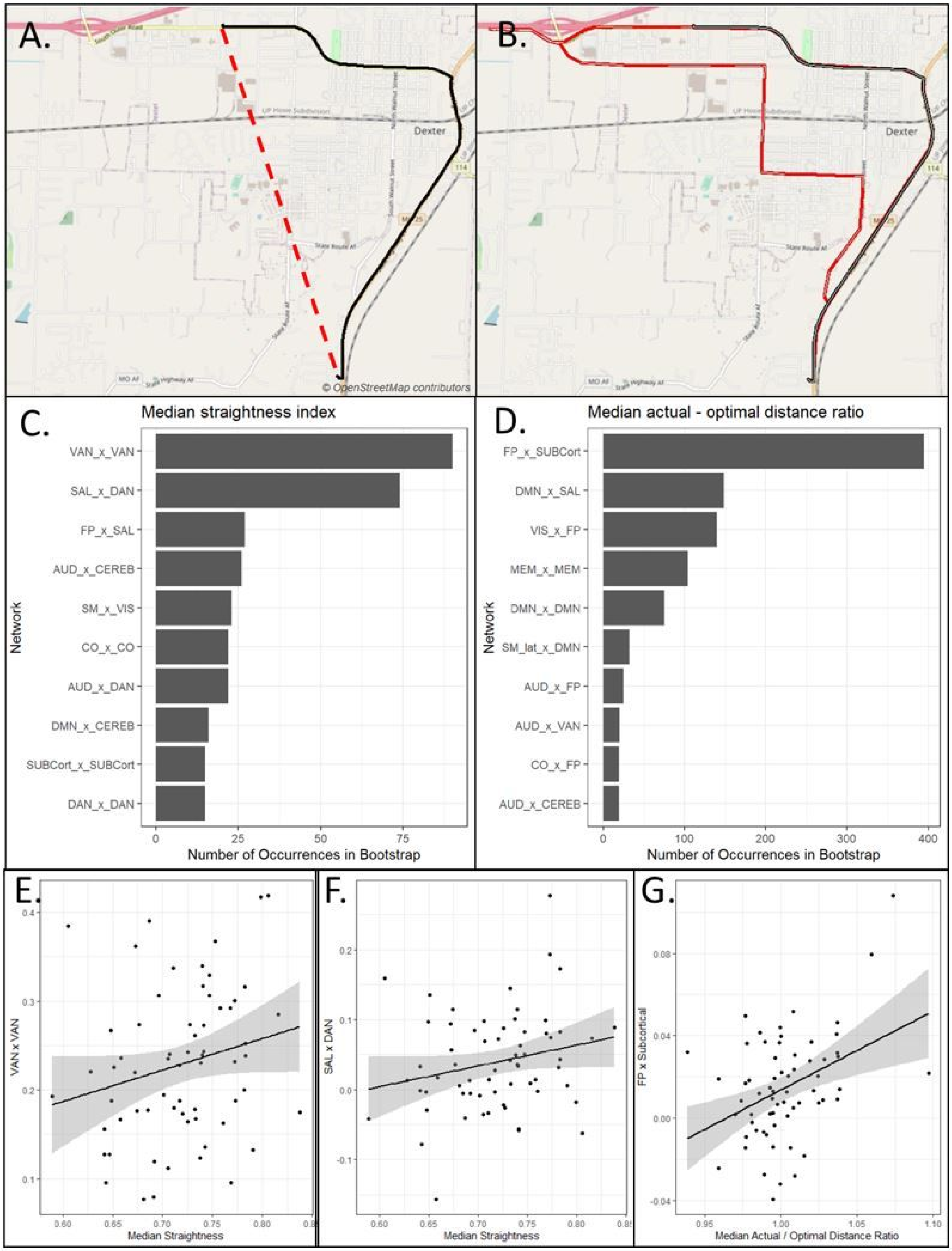

Figure 2

(A) Route straightness was calculated by taking the Haversine distance (shown in red) divided by the actual route (shown in black) distance (B) The actual – optimal distance ratio was calculated by dividing the length of the actual route (shown in red) divided by the optimal route (shown in black). The actual route driven was estimated using the coordinates from each 30s epoch breadcrumbs from the ODB-II chip. The optimal route was generated by using Open Street Map. For this example, the actual route driven was six miles, while the optimal proposed route was four miles. The actual – optimal distance ratio for this particular route was 1.5. (C) The networks most frequently utilized for prediction of the median straightness index were the intranetwork ventral attention network connection (VAN x VAN) and the salience – dorsal attention network connection (SAL x DAN). (D) The network most frequently utilized for prediction of the median actual – optimal distance ratio was the frontoparietal – subcortical (FP x SubCort) network connection. (E) There was a positive correlation between the VAN x VAN connection and median route straightness. (F) There was a positive correlation between the SAL x DAN connection and median route straightness. (G) There was a positive correlation between the FP x SubCort connection and the median actual – optimal distance ratio

Supplementary Files

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- SupplementalMaterials.docx