Cognitive Route Planning in Vehicle using Artificial Neural Network

Yousaf Saeed[†], Khalil Ahmed[††], Sagheer Abbas[†††], Atifa Athar[††††], Asim Zeb[†††††]

]University of Haripur, Pakisan; Konsortium Pakistan; NCBA&E, Lahore Pakistan; CIIT Lahore, Pakistan Qurtaba University Peshawar, Pakistan

Summary
Department of transportation worldwide is facing various challenges despite introducing and incorporating number of vehicular features. However, addressing human cognition in vehicle is very much necessary for the future so that vehicle can provide human-like decisions in different situations. In this regard, providing accurate, shortest, timely and optimal route information to the driver of vehicle in a cognitive manner is indeed important. This is different from the current vehicle route information schemes that is provided on demand, is typically static and do not evolve. The proposed cognitive scheme discussed in this paper enables a vehicle to provide optimal route information to the driver by utilizing cognitive parameters. We have proposed route planning scheme to be planned by vehicle itself from cognitive perspective where cognitive memories and cognitive variables both are utilized. Cognitive memory is going to be essential for storing route experiences related to different task environments. Also, route episodes are learned, stored and accessed later inside cognitive memory for optimal use. This enables a vehicle to evolve itself with route information and provide rational routes. Cognitive variables facilitates the route related planning approach in this regard. The more a vehicle plan routes, the more it populates its knowledge repository with time. The goal is to make a shift from supervised learning mode towards unsupervised ultimately. Moreover, in the proposed scheme, concepts of controllers are introduced from system administration point of view for performance enhancement, and for validation of the proposed scheme, artificial neural network is used to highlight that learning can be achieved in vehicular agency for providing optimal routes cognitively.
Keywords:
Vehicle route, GPS, VANET, ANN, Cognitive Memories

1. Introduction

To carry out an effective journey in vehicle, the use of GPS [1] is very much essential as it provides route information of all possible landmarks/ structures that might include number of intersections, traffic lights, restaurants, schools, markets etc. and information such as weather, traffic and road conditions [2]. Route input to the GPS might be in the form of voice patterns [3], touch responses (touch screens), braille for disabled users etc. All these features provide good use of GPS when use in vehicle, therefore, vehicles are being equipped with in-vehicle GPS navigation. The GPS is composed of three segments i.e. space segment that consist of satellites, control segment covering ground stations and user segment which consist of a user and its GPS receiver [4]. The navigation performed is static and therefore, provide no updated information once the signals are lost.

The current onboard GPS vehicle navigation system functions by receiving signals from satellites, detects vehicle location via GPS antenna and GPS receiver. It detects vehicle direction through the direction sensor. Also, it detects vehicle travel distance via speed sensor. All these information from the antenna and sensors are checked against the map database and is then displayed on car navigation system screen. In-vehicle GPS connectivity with satellites is shown in Fig.1.

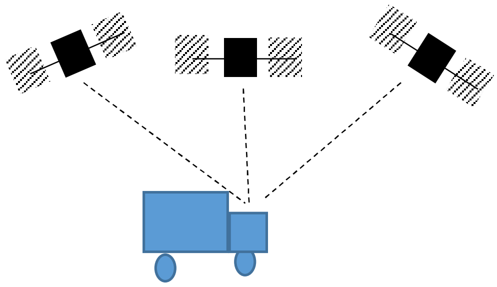

Fig.1: Current in-vehicle navigation system connectivity with satellites

The current route searching mechanism in vehicle is performed in this manner: vehicle's current location is identified, destination of the driver is searched, route to destination is checked, recommended route is suggested, directions are provided for the selected route and finally, route-related information is displayed on screen. It is important to mention that such total dependency on vehicular GPS for entire life time is not a good option indeed as on 25-26[th] February 2016, the GPS users faced

Manuscript received March 5, 2026
Manuscript revised March 20, 2026
https://doi.org/10.22937/IJCSNS.2026.26.3.7

an anomaly in operations [5] when information was broadcasted by multiple satellites for several hours regarding the offset between GPS time and coordinated time universal (UTC) in a way that did not conform to the GPS signal interface specification (IS-GPS-200 [6]) [7]. This takes us to adopt other strategies along with GPS navigation.

One strategy or scheme is to use human cognition in vehicle [8] for route management so that there would not be total dependency on GPS for providing route information every time. Cognitive memories are important in this aspect [9]. Utilizing sub-categories of human memory structure [10] in the form of working memory [11], short-term memory [12], long-term memory [13], associative [14], semantic [15] and episodic memories [16] [17] are essential for rational decision making which can be in the form of providing optimal route information. Also, every iteration (route) need to be learned and recorded. The proposed system makes use of these cognitive memories for attaining better route results. The proposed cognitive memory is shown in Fig.2.

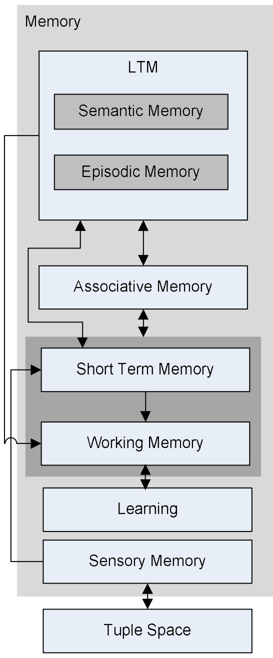

Fig.2: Proposed Cognitive Memory for Route Planning

2. Proposed System

In the proposed route planning module, when route input is provided, categorization takes place whether it is an invalid route, existing route or a new route. If wrong input is provided in the form of incorrect destination, the route input is treated as an *invalid route*. If a vehicle already travelled from a specific source to a certain destination on a specific route, and the vehicle again has to travel from the same source to the same destination, the route is treated as *existing route*. If a vehicular memory does not have previous episode of the source and destination, the route is considered as a *new route*. In case of existing route, there is always the case that the desired journey can be made successful by using the information from vehicle memory, i.e. the information received from the vehicle memory is enough for a successful journey. However, still fresh information is required for optimal route notification. Also, if communication fails or a VANET node is not available, memory info is utilized although not optimal but sufficient enough. For new route, the involvement of communication with the third party is required, as without that related information associated with the input route will not be available.

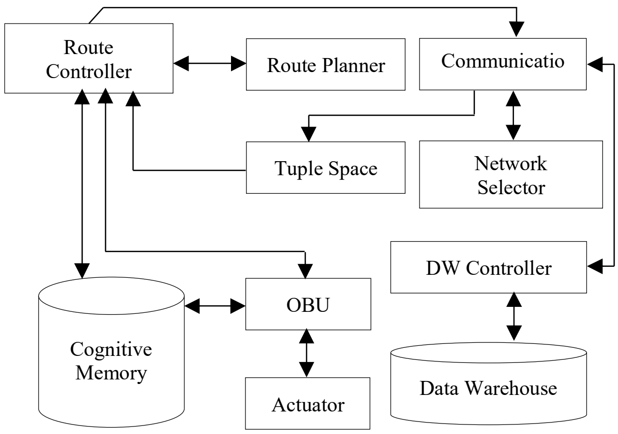

Fig. 3: Proposed Route Planning Module

Fig. 3 indicates route planning module for providing optimal route to the user/ driver. The on-board unit receives the input route information and activates the route planning module by sending a signal to the route controller.

The route controller assigns appropriate tags to both source and destination and sends the tagged information to route planner unit which checks to see whether the given input is right or wrong by comparing it with a route profile. If the given inputs is incorrect, the user is notified accordingly to provide the route input once again. If the given input is correct, route controller is updated. Route controller directs the route input to the memory unit to find its category. The memory checks the presence of a previous recorded episode. If it exists, the route is treated as existing route and if it does not exist, the route is considered as new route. The route controller receives the route category and sends it again to the route planner. The route planner tag the required information to be ready for information update purpose, and hand it back to route controller to initialize communication module for outside intervention. Communication unit selects the appropriate protocol and network selector selects suitable network for communication. Vehicle is equipped with several network technologies that include Wireless Access for Vehicular Networks (WAVE)/ Dedicated Short Range Communication (DSRC), WiFi, Mobile-Worldwide interoperability for Microwave Access (MWiMAX), Long Term Evolution (LTE), cellular and satellite.

Communication is made with data warehouse which is received by the data warehouse controller. It inspects the requested info and forwards it to the appropriate data mart for retrieval. The updated required information is sent back to communication module of the requested vehicle. This information need proper organization, therefore, it is transferred to the tuple space unit which properly organizes it. The organized information is presented to the route controller. The information is given to the on-board unit for decision. The on-board unit notifies the user/driver about the updated route information via actuator. The actuator acknowledges the on-board unit. This whole process of user input and route update is sent to vehicular memory for episode recording.

If the route is identified as a new route, vehicle can avail the following options based on priority scheme.

- If communication module fails then based on pre-map information (already stored map info) in memory is utilized and the journey is made possible.
- If communication module is functioning, updated route info is retrieved by consulting semi-supervised or supervised stations.

It is important to mention that in both the cases of existing or new route, optimality is achieved when regular updation of routes takes place.

3. Module Case of Existing Route Identification during Route Planning

Route planner provides the user (driver) the shortest possible and updated route towards destination. The route need to be known before traveling to destination, therefore, route identification by vehicle is necessary. Also, in case of incorrect route input, vehicle reports it as invalid route.

Route input which is given by the user is processed through OBU while supported by route controller and memory process. Process flow for this module case is shown in Fig. 4 which shows its functionality with respect to time intervals t_n. Also, in Fig. 3, the proposed components can use different algorithms such as OBU can use preemptive real-time scheduling algorithm, route planner can make use of ant colony optimization algorithm, cognitive memory can utilize SURF algorithm, and communication controller can use geographic routing protocol.

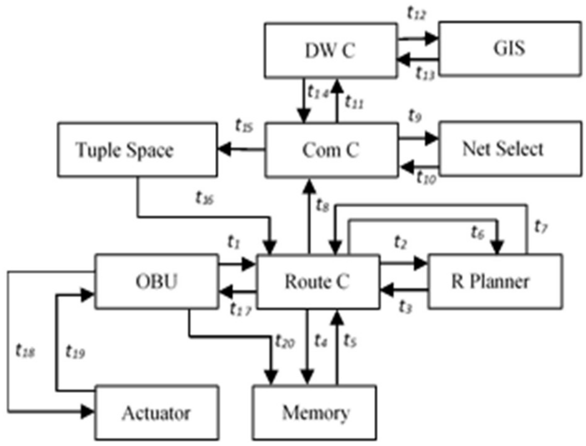

Fig. 4: Process Flow of Route Identification, updation and learning via cognitive memory

Cognitively this case can be explained as, when a person want to go from his Regent Street office to

Gatwick Airport in car to pick his family. Upon receiving the route destination as the Gatwick airport. The vehicle detects the destination as a valid input. The vehicle selects the shortest route which contains five intersections with two traffic lights control systems, one petrol station and one mechanic shop in between source and destination. It took 45 minutes for the car to reach to the destination. Suppose after three months, the person again has to travel from Regent Street office to Gatwick Airport. This time the route is treated as existing route by the vehicle because of having previous route experience in the memory, so just route updation takes place. Upon route updation, it is found that the same route now contains five intersections equipped with three traffic lights control systems, two petrol stations, three mechanic shops and one restaurant. It took 35 minutes for the car to reach to the destination.
Now consider after few weeks, the person once again has to travel on the same route and communication component of the vehicle is unable to work due to some issue as malfunction for instance, however, the driver gets the updated information of the route from vehicular cognitive memory because of the existence of the two episodes. It took 35 minutes for the car to reach to the destination.

During these months, three episodes are generated for the same route, which is learned and finally recorded in vehicular cognitive memory. With experience, vehicular memory populates the updated route information. The experience gained lets the driver/user aware of the updated information of the chosen route in case of some issue such as if communication component of the vehicle is not working and external communication is not possible.

During user route input, if the route is incorrectly spelled for instance, the user is notified to input the route correctly or appropriately. This makes the user properly synchronized with the vehicular input system.

4. ANN Simulation

Now we are going to use ANN to train the network based on our proposed dataset of 2048 elements. Objective here is to minimize the error rate during the training. Neural network fitting tool is used and inputs and output files are assigned. Inputs 'Case3inputs' is a 2048x11 matrix, representing static data: 2048 samples of 11 elements while Targets 'Case3outputs' is a 2048x1 matrix, representing static data: 2048 samples of 1 element. Table 1 indicates the proposed eleven input variables with cognitive variables (highlighted) that impacts the provided final output variable. These parameters are considered for artificial neural network simulation.

Table 1: Proposed Variables for the dataset containing Eleven Inputs and One Output having three cognitive variables (highlighted)

Route Input Detection	Route Profile	Route Category	Infrastructure Info	Error Probability	Previous Behavior
Uncertainty	Protocol Relevancy	Wifi	GIS	Data Organization	Optimal Route Information

Fig. 5 highlights three kinds of samples. For training, 1434 samples are selected for training the network and the network is adjusted according to its error. For validation, 307 samples are designated where training is halted when generalization stops improving, and finally for testing, 307 samples are selected which shows an independent measure of the network performance.

Fig. 5: Distribution of Samples in Neural Network for Training, Validation and Testing

After the division of samples, number of hidden neurons are selected as 10 and continued. Fig. 6 indicates 11 inputs with 10 hidden layer neurons, 1 output layer neuron and desired output as 1.

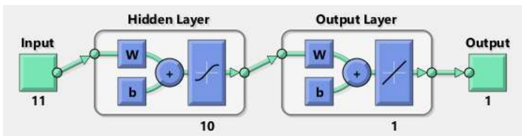

Fig. 6: Generated Neural Network

Subsequently, the network is trained using Levenberg-Marquardt back-propagation algorithm and results are achieved as shown in Fig. 7 where the number of epochs are indicated horizontally and mean square error vertically. Mean Squared Error is the average squared difference between outputs and targets. Lower values are considered better and zero means no error. This figure does not show any major problem with the training. Validation and test lines are very much similar as if the test line had increased significantly before the increase of validation line then some overfitting might have taken place. Here the decrease of error is seen during training, validation and testing data which are represented in different colors. It is found that when the training is carried out, the error keeps on decreasing and at epoch 31 best validation result is achieved which is 0.0011484.

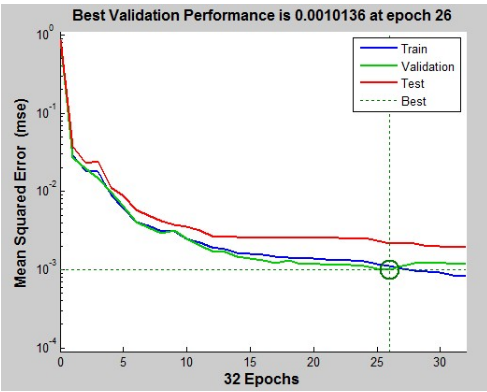

Fig. 7: Performance graph indicating the Lowest Error

Also, the error histogram generates a normal distribution making a bell like structure with lowest errors as defined in Fig. 8.

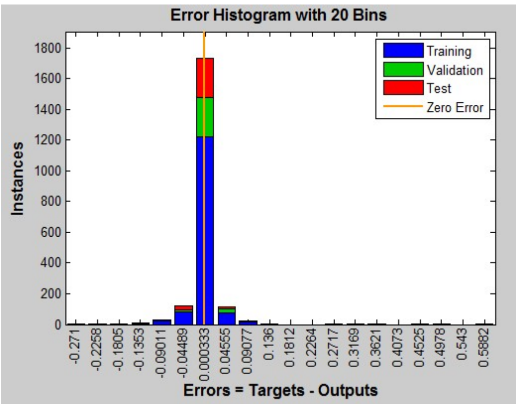

Fig. 8: Error Histogram

Moreover, the plotted regression plot indicates training, validation, testing and overall performance separately. Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship. The value of R is greater than 0.96 and indicated in Fig. 9.

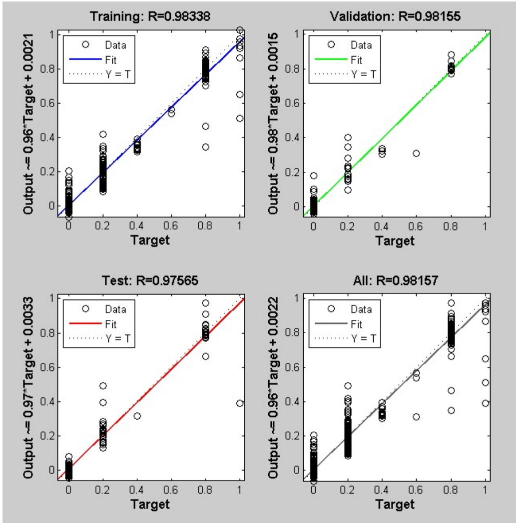

Fig. 9: Regression Plot

5. Conclusion and Future Work

In the module case, input route is provided by the user which is considered as a valid input. Upon inspecting, the input route is categorized as existing route. The existing route information is enough for the user to start moving to the destination, but not optimal enough due to the rise of environmental and structural changes from time to time. Requirement of the update of infrastructure is required between source and destination. Data warehouse is contacted and the most recent infrastructure information is delivered to the user. The data management issue can be resolved by the use of *preemptive real-time scheduling* as the OBU and route controller has to deal with multiple requests in real-time. For selecting shortest path from source to destination, *ant colony optimization algorithm* might be used. For acquiring GIS data, communication protocol to be used can be in the form of *geographic routing protocol.*

From cognitive perspective a human mind also makes decision with sensory signals and information availability. Category to an event is also assigned by the human mind to the processed patterns, however, at times the assignment of category to an event might not be correct due to other parameters as uncertainty. So positive result is not always generated as both negative and positive results are part of the experience. The impact of cognitive variables supports the case from cognitive point of view. The instances involved during the whole process of this case from user input till the optimal route information delivery is recorded as one episode in the memory. This experience is important, as if communication module is not functioning in semi-supervised mode then cognitive memory is used for request completion as unsupervised, thus elaborating the objective of making vehicular memory unsupervised. The process elaborated semi-supervised behavior however.

For artificial neural network, a dataset containing 2048 elements is used. The elements/ variables in this dataset contain both static and cognitive variables so that cognition. When the network is trained with our proposed dataset, decrease of error results proves that when the proposed network can learn with time and can be evolved when cognition is incorporated and the system shifts gradually from supervised to unsupervised. For future work both the incorrect route input scenario and route profile will be discussed. Again in each step, instances involved during the whole process are created and recorded as episode ultimately. When these episodes are populated, experience is gained thus resulting better decision making ultimately.

References

[1] T. Logsdon, The Navstar Global Positioning System, Springer Science, 1992.

[2] Q. K. J. X. E. C. Benjamin Zeeb, "Development of landmark based routing system for in-car GPS navigation," in *7th International Conference on Digital Ecosystems and Technologies (DEST)*, 2013.

[3] C. E. Karpagavalli. S., "A Review on Automatic Speech Recognition Architecture and Approaches," *International Journal of Signal Processing, Image Processing and Pattern Recognition* , vol. 9, no. 4, pp. 393-404, 2016.

[4] "Remote sensing and GIS application," 2014. [Online]. Available: http://ecoursesonline.iasri.res.in/mod/page/view.php?id=124964.

[5] K. M. B. G.-S. Jeong Jae-Hoon, "Position Recognition for an Autonomous Vehicle based on Vehicle-to-Led Structure," in *Recent Advances in Electrical Engineering and Related Sciences*, AETA, 2016.

[6] "GPS Direcrorate Systems Engineering & Integration Interface Specification (IS-GPS-200)," Navstar, 2016.

[7] P. J. E. D. B. R. Karl Kovach, "GPS Receiver Impact from the UTC Offset (UTCO) Anomaly of 25-26 January 2016," GPS.gov, 2016.

[8] M. A. B. H. a. M. B. Sven Kraus, "Cognition and Emotion in Autonomous Cars," in *IEEE Intelligent Vehicles Symposium*, 2009.

[9] J. Sweller, "Working Memory, Long-term Memory, and Instructional Design," *Journal of Applied Research in Memory and Cognition,* vol. 5, no. 4, pp. 360-367, 2016.

[10] L. Mastin, "Types of Human Memory," 2010. [Online]. Available: http://www.human-memory.net/types.html.

[11] D. C. N. J. L. Phillips, "A biologically inspired working memory framework for robots," in *ROMAN 2005. IEEE International Workshop on Robot and Human Interactive Communication, 2005.*, 13-15 Aug. 2005.

[12] G. A. B. M. V. A. T. V. Ananda L. Freire, "Short-term memory mechanisms in neural network learning of robot navigation tasks: A case study," in *Robotics Symposium (LARS), 2009 6th Latin American*, Valparaiso, 29-30 Oct. 2009.

[13] F. B. P. C. B. S.-D. R. J. D. R. Salgado, "A procedural Long Term Memory for cognitive robotics," in *2012 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS)*, Madrid, 17-18 May 2012.

[14] T.-Y. K. Chae-Wook Chung, "Associative memory network controller for robot manipulators with generalized trajectory learning ability," in *1997 IEEE International Conference on Systems, Man, and Cybernetics, 1997. Computational Cybernetics and Simulation*, Orlando, FL, 12-15 Oct 1997.

[15] A. R.-C. Sébastien Dourlens, "Semantic Memory for Pervasive Architecture," in *Information Computing and Applications*, Springer Berlin Heidelberg, 2010, pp. 94-102.

[16] B. S. A.-H. T. J. A. S. Wenwen Wang, "Neural Modeling of Episodic Memory: Encoding, Retrieval, and Forgetting," *IEEE Transactions on Neural Networks and Learning Systems,* vol. 23, no. 10, pp. 1574 - 1586, 06 August 2012.

[17] A. G. R. L. R. V. T. Deutsch, "Episodic memory for autonomous agents," in *2008 Conference on Human System Interactions*, Krakow, 25-27 May 2008.