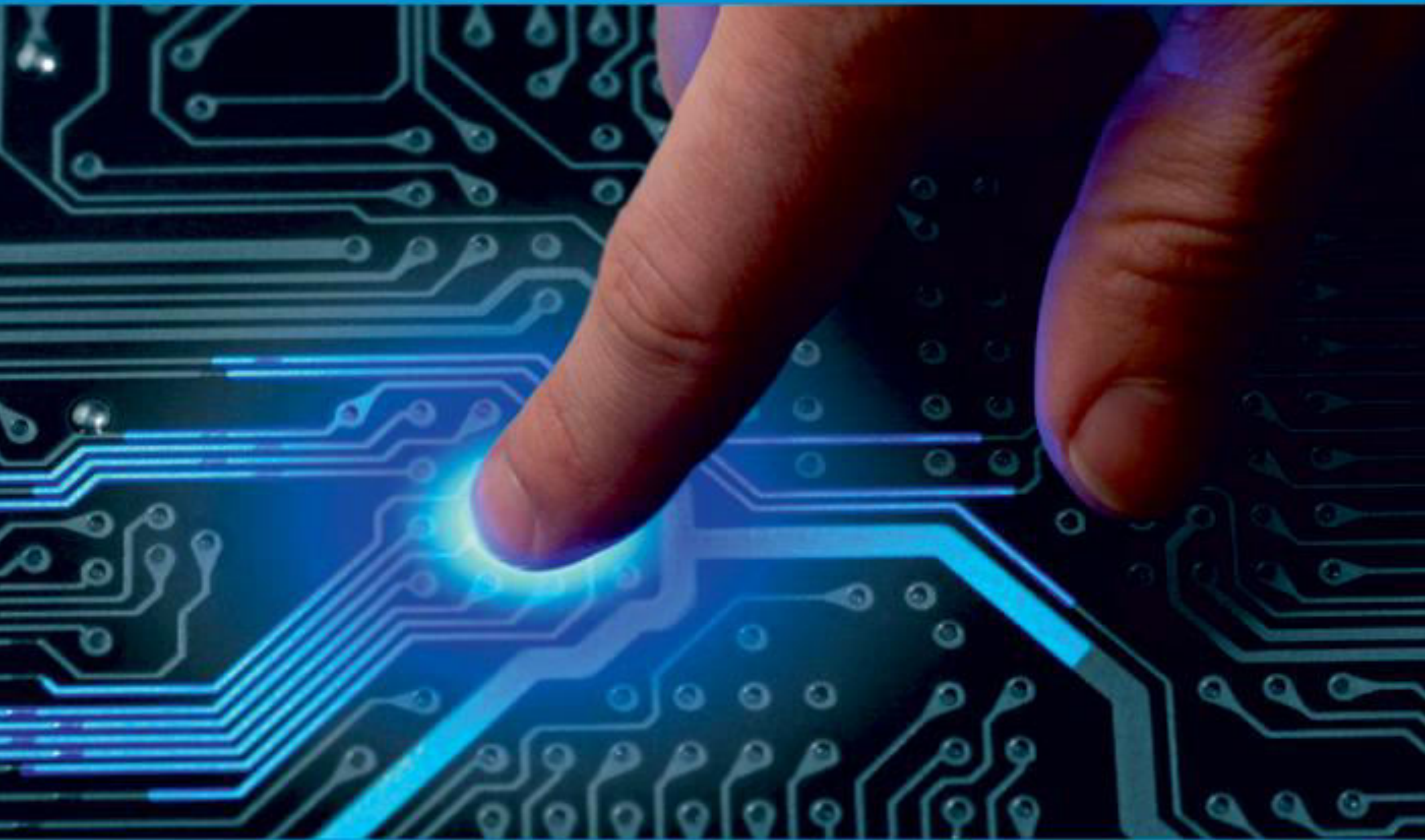
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 7, July 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107071 |

Personalized Route Selection using Machine Learning

Joel Thomas Chacko

UG Student, Dept. of C.S., MVJ College of Engineering, Whitefield, Bengaluru, India

ABSTRACT: Personalized route selection is proposed and constructed in this work using machine learning techniques to tailor the map routing algorithm to the preferences of the user. The proposed routing algorithm is attempted to incorporate a psychological component through this work. Using machine learning techniques, it is attempted to identify the preferences of users based on information about their daily commutes. The course the client likes on an everyday premise can be relied upon factors like plant life, presence of water bodies, lanes and so forth; this expansion makes the current A* algorithm's routing more amiable and affable to the user. This algorithm enables the user to select a path that is both the quickest and the type of road they prefer to commute on, despite the fact that the user can traverse using a variety of routes from the source to the destination. For example, a client could favor a cross-country component in his movements; Based on the user's previous choices, the algorithm determines this information and suggests roads that contain it. Based on simulations and actual tests, this work's proposed algorithm adds personability, stability, and high efficiency. The Personalized Route Selection using Machine Learning's improved routing algorithm can be deployed in the contemporary maps technologies as an additional feature making travels a likable experience.

KEYWORDS: Personalized Routing, User Preference (Psychological Element), Machine Learning, Improvised A* Algorithm, Multivariable Linear Regression

I. INTRODUCTION

This work proposes and designs a Personalized Route Selection using Machine Learning Techniques which personalizes the map routing algorithm according to the individual's desires. There are a couple of notable contributions in this domain, namely a paper that addresses the issue of path planning for intelligent driving cars in situations involving restricted driving, traffic jams, and accidents, this work suggests and implements a best path selection algorithm [1]. This algorithm predominantly helps intelligent devices in their driving automation. Another study offers a novel approach for selecting the best path for intelligent driving cars to address the hot research topic of path planning of such vehicles in emergency situations. We created a hybrid algorithm based on the prior knowledge applied reinforcement learning strategy and the searching-optimized A* algorithm to assist intelligent driving vehicles in choosing the best path in the traffic network in emergencies such as limited height, width, weight, accident, and traffic jam [2].

Recursive logit, a type of inverse reinforcement learning, is used by the transportation research community for route choice modelling. In this discipline, an agent's purpose is learned by observing its behavior. It enables estimation of an ideal (negative) reward function in a computationally efficient manner that works for large networks and a large number of observations by solving a large-scale system of linear equations [3]. Drivers typically determine their routes in transit networks based on their own understanding of the network. The prior trips of drivers provide this knowledge. When faced with traffic, vehicles may alter their routes to seek a speedier option. However, given that other drivers can take the same route, this rerouting might not be the best option. Additionally, similar actions can cause delays in other links. On the other side, the system as a whole might profit if drivers plan their routes with the goal of maximizing the total travel time (system's utility), rather than their own personal journey time (agents' utility) [4].

When confronted with traffic congestion or when advised that delays are anticipated along their planned routes, human drivers may replan. Previously unaddressed, the impacts of drivers rerouting are discussed in this work. In order to determine if this type of co-adaptation can cause interferences or beneficial cumulative effects, we examine re-routing situations while also taking adaptive traffic signals into consideration. We employ an abstract route selection scenario that shares many characteristics with real-world networks. The outcomes of our trials demonstrate that rerouting does, in fact, pay off globally since the network's total load is balanced. Rerouting is also helpful to make up for a potential lack of adaptability in terms of traffic management [5].

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107071 |

II. RELATED WORK

There are several notable contributions made in this domain of optimizing routing algorithms in order to improve the efficiency and reliability. Couple of the notable contributions are: This paper sheds light on our society's growing need for mobility, which presents a number of difficulties for traffic engineering, computer science in general, and multiagent systems in particular. Since adding more capacity is not an option, it is vital to make better use of the transportation infrastructure that is already in place [6]. To account for diverse contexts and sensor qualities, it is impossible to solve this issue via stacking decision rules. For these situations, learning-based control techniques are adaptable [7]. Memory is a vital tool for intelligent thinking in partially viewable contexts. Despite its significance, Deep Reinforcement Learning (DRL) agents have so far relied on very basic memory structures, with an LSTM layer or a temporal convolution over the previous k frames serving as the primary techniques for overcoming partial observability [8]. We apply the principles behind Deep Q-Learning's success to the continuous action domain. We describe an actor-critical, model-free algorithm that may work over continuous action spaces and is based on the gradient of a deterministic policy. Our approach successfully completes more than 20 simulated physics tasks, including well-known issues like cartpole swing-up, dexterous manipulation [9].

In order to increase the effectiveness of path selection, we aim to develop a pre + during trip path prediction model based on the effects of external and internal information on path choosing behaviours [10]. For the successful implementation of intelligent transportation systems, accurate and timely traffic flow information is essential. We have officially entered the big data era of transport thanks to the explosion of traffic data over the past few years. Many real-world applications are still unsatisfied with current traffic flow prediction techniques, which primarily use shallow traffic prediction models [11]. Location-based social networks (LBSNs) are expanding quickly along with social networks and wireless communication technology. Users may receive a fresh point-of-interest (POI) from location-based social networks that offer personalized location service [12]. This study suggests a model-free deep reinforcement learning (DRL) algorithm for selecting the best route and charging stations (RCS) to address the challenges of traffic circumstances and dynamic arrival charging requests [13]. The prediction of travel times is a difficult challenge for Intelligent Transportation Systems (ITS). Drivers can make more informed route decisions if they have accurate travel time information. In consequence, this reduces traffic congestion and boosts operational effectiveness. There are numerous methods for predicting trip times, however the majority of them are based on shallow learning frameworks [14].

We deal with the issue of online coordination for connected and autonomous vehicles (CAVs) to pass two nearby crossroads in an urban setting. In order to minimize fuel usage, we provide a decentralized optimal control framework whose solution yields for each vehicle the best acceleration or deceleration at any given time [15]. According to the user's interests, personalized travel route suggestions will suggest tourist attractions and create routes, which can be thought of as a recommendation and sequence task. There are significant issues in determining how to construct an interest model for users to identify individualized attractions and produce the location sequence. In this study, user interests are discovered and route features are modelled using multi-source social media [16]. As cities grow, intercity highways become increasingly important for daily travel. Road management and participants are becoming more and more concerned with how traffic is moving on the highway network. However, precise traffic flow forecast is difficult to achieve due to the influence of the highway network topology and additional features like weather. Building a multidimensional feature matrix and predicting the network's traffic flow simultaneously is challenging [17]. In a variety of applications, including those related to space, transportation, industry, and defence, an intelligent autonomous robot is necessary. Additionally, mobile robots are capable of handling materials, providing disaster relief, patrolling, and conducting rescue operations. As a result, a mobile, autonomous robot that can move freely in both static and dynamic environments is needed. The basic purpose of mobile robot navigation is to move the robot from its starting point to its destination position safely and smoothly while producing the best possible path length. Researchers have looked into a number of techniques for designing the navigation path of robots in this regard [18].

By reducing the use of private vehicles, an intelligent transport system (ITS) can ease traffic congestion on roads. In order to accomplish the same, we must upgrade the current infrastructure in the targeted area; but, doing so would take a lot of time and money. However, to create an effective public transit system, technologies like the Internet of Things (IoT) can be combined with the currently installed infrastructure [19]. Mobile robots can be used for exploration in an unfamiliar environment. We described a reinforcement learning technique in this research with the goal of resolving the exploration problem in a corridor setting. The only input for the learning model was the depth image from an RGB-D sensor. Through the use of a convolutional neural network model that has already been trained, the depth image's feature representation was recovered [20]. For police to track vehicles, in particular, automatic vehicle classification is essential to an intelligent transportation system. Image-based vehicle classification in real-world settings is still a difficult task, and the performance is far from optimal, due to the complicated lighting and image capture conditions. The human vision system, in contrast to the computer vision system, demonstrates amazing aptitude, particularly in processing nuances, according to the mechanism of visual attention [21]. In order to regulate and track single and multiagent systems optimally, this paper evaluates the current state of the art in feedback control techniques based on reinforcement learning (RL). We'll go through existing RL solutions for graphical games, as well as optimal H 2 and H control problems. RL approaches use measured data throughout the system

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107071 |

trajectories to learn the solution to optimum control and game problems online. As fundamental algorithms for discrete-time (DT) and continuous-time (CT) systems, respectively, we explore Q-learning and the integral RL method [22].

III. METHODOLOGY

The methodology of this proposed algorithm receives the following as inputs: 1. Historical data of every day path selection of the user and this information is stored to deduce preferences of the user while traveling. It can either be the shortest path, or any other component favoured by the user; 2. Traveller's socio-economic conditions are noted; 3. Prevalent traffic conditions as well - these two inputs are used to discover the possible routing using the contemporary routing algorithms.

The available routes generated by the primary processing and the secondary processing are combined and an optimal routing path is selected for the user to commute in. The Adaptive Route Selection using Machine Learning's improved routing algorithm can be deployed in the contemporary maps technologies as an additional feature making travels a likable experience.

The objectives of the following work are:

- Personalized Routing Algorithm
- More Efficient Map Routing
- Improvised A* Algorithm
- Considers Users' Route Preferences
- Adds a Psychological Element to the Existing Routing Algorithm.

The various existing systems have the following characteristics, and they are: the contemporary map routing algorithms do not account for the user route preferences; a data structures algorithm - the A* shortest path routing algorithm without a machine learning element is the existing technology used; the roads aren't labeled by the physical attributes it contains. The corresponding demerits of the following systems are: the route preferences aren't considered by the algorithm based on the route labels (the physical attributes of the road, like the presence of water bodies, boulevards etc); this algorithm also labels roads/routes by the physical attribute it contains.
The below shown diagram represents the flowchart of this work. Consider the below shown flowchart.

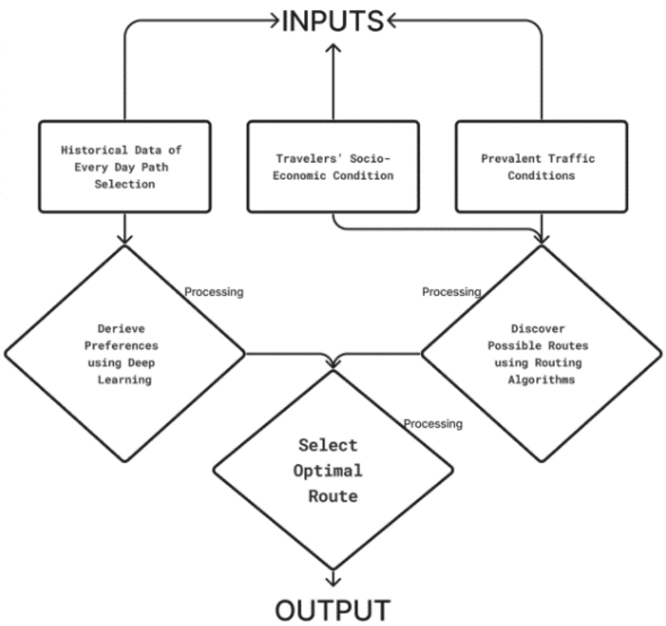


Fig. 1. Flowchart

The comparison between the existing system and the proposed system are:

- The current routing technologies does take into consideration the user habits like preferred mode of transportation etc, however the proposed system takes into consideration the psychological component behind the user's route selection.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107071 |

- The labeling of routes based on the physical attributes like the presence of water bodies, greenery, boulevards etc.
- The proposed system performs the labeling of routes according to the physical attributes as seen in it.
- The proposed system adds a modification to the A* shortest path routing algorithm which selects the routes based on the shortest distance and cost taken to arrive at the destination from the source. The modification is the addition of the user's preference (psychological element) to the above mentioned algorithm.

The advantages of the proposed system are: The proposed routing algorithm takes into consideration the user habits like psychological component behind the user's choice of routes etc; the present system makes no such inclusion. The proposed system also attempts to label the routes based on the physical attributes seen in it - this makes the user's travel personable and enjoyable. There is a modification made to the existing A* Algorithm which adds a psychological element to the user's choices, which is deduced by the Machine Learning Algorithm.

The scope of this work is to give the users a more personable, customized choice of travel over the contemporary map technologies; and an attempt is made to overcome the limitations of the existing systems. The following are the methods used for the same.

A. Improvised A* Algorithm

The A* Algorithm is predominantly used in graph traversals and path finding, and is one of the algorithms used by contemporary map routing. In the improvised version of the A* algorithm, we take into consideration the psychological component behind the user's choice of routes. One of the heuristics used to calculate the distance in this particular algorithmic modification is called the Manhattan Distance Heuristic. Consider the below shown diagram [22].

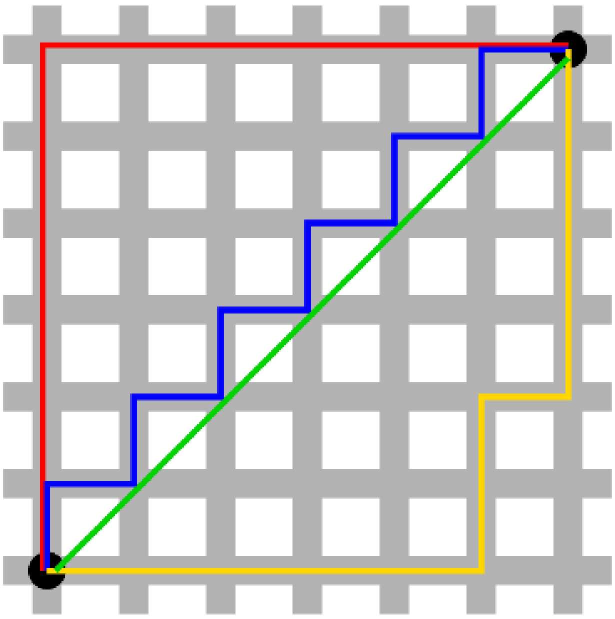


Fig. 2. Manhattan Distance Heuristic

Since the target square must be reached from the present square by moving a total number of squares both horizontally and vertically, this technique of finding h(n) is known as the Manhattan method. Any diagonal movement and potential obstructions are disregarded.

$$H = |x_{start} - x_{destination}| + |y_{start} - y_{destination}|$$

B. Route Labeling

For the Machine Learning Algorithm to draw conclusions about the user's preferred mode of commuting, the routes primarily must be labeled. The route labeling gives the machine learning algorithm the inputs it needs

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107071 |

to deduce the user's preferences. For example, the presence of water bodies, greenery etc can be indicated by percentages.Thereby making it possible for the Machine Learning Algorithm to bring about conclusions.

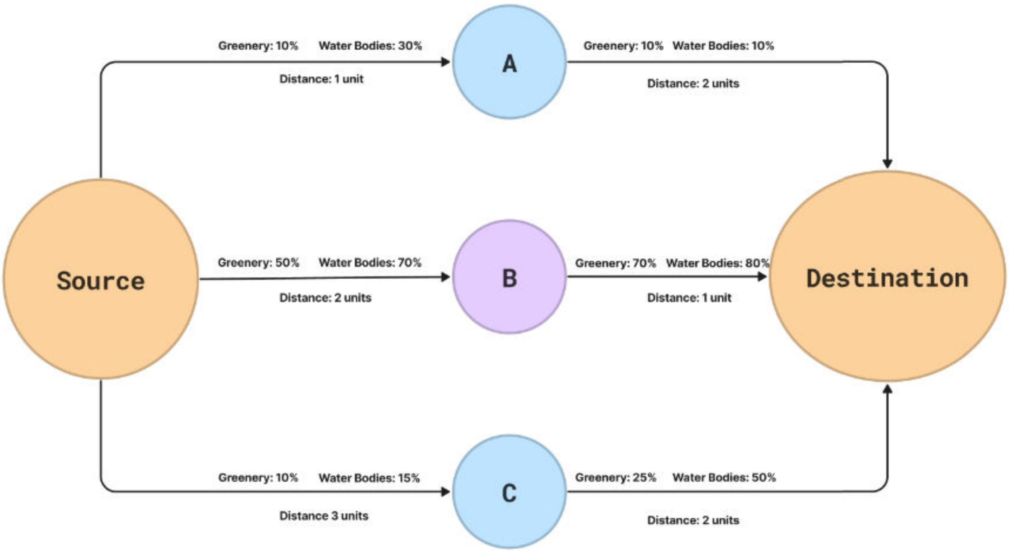


Fig. 3. Route Labeling

C. Regression to Estimate the Cost Functions for the Path

In order to demonstrate the link between two variables, linear regression applies a linear equation to the observed data. The idea is that one variable acts as an independent variable and the other as a dependent variable. For instance, a person's weight and height are linearly connected. This demonstrates a linear link between a person's weight and height. The person's weight increases in proportion to their height.
The linear relationship between two variables is displayed via linear regression. The slope formula that we previously learnt in prior classes, such as linear equations in two variables, is comparable to the equation of linear regression. It comes from;

Y= a + bX

Here, we need to determine the intercept (a) and slope (b) of the line that is drawn in a scatter plot.

$$a = \frac{[(\sum y)(\sum x^2) - (\sum x)(\sum xy)]}{[n(\sum x^2) - (\sum x)^2]}$$

$$b = \frac{[n(\sum xy) - (\sum x)(\sum y)]}{[n(\sum x^2) - (\sum x^2)]}$$

Here Linear Regression is used to estimate the cost of the route when a user decides to travel on it; lower values of cost are generally preferred. Linear Regression seems elementary for this problem statement; but it conveys the idea in its essence.

IV. SIMULATION RESULTS

The below shown outputs show a simulation of the mentioned personalized route selection. The output shows a searching algorithm that functions on A* algorithm, simulating a real-time map routing. The course the client likes on an everyday premise can be relied upon factors like plant life, presence of water bodies, lanes and so forth; this expansion makes the current A* algorithm's routing more amiable and affable to the user. This algorithm enables the user to select a path that is both the quickest and the type of road they prefer to commute on, despite the fact that the user can traverse using a variety of routes from the source to the destination [23].

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |
|| Volume 11, Issue 7, July 2023 ||
| DOI: 10.15680/IJIRCCE.2023.1107071 |

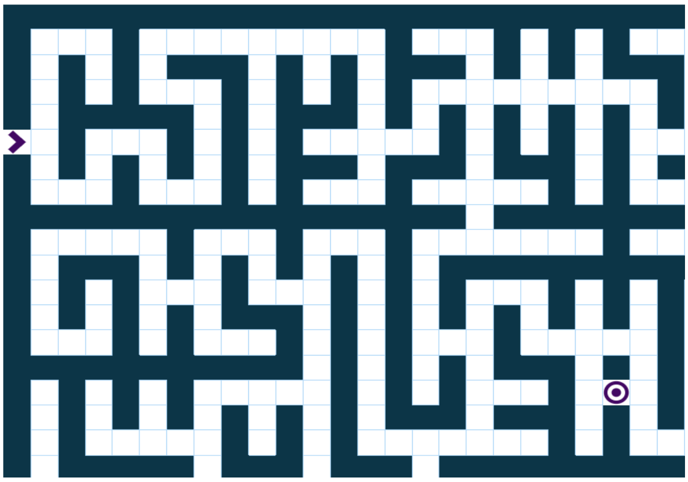


Fig 4. A* Algorithm with Source Node and Goal Node

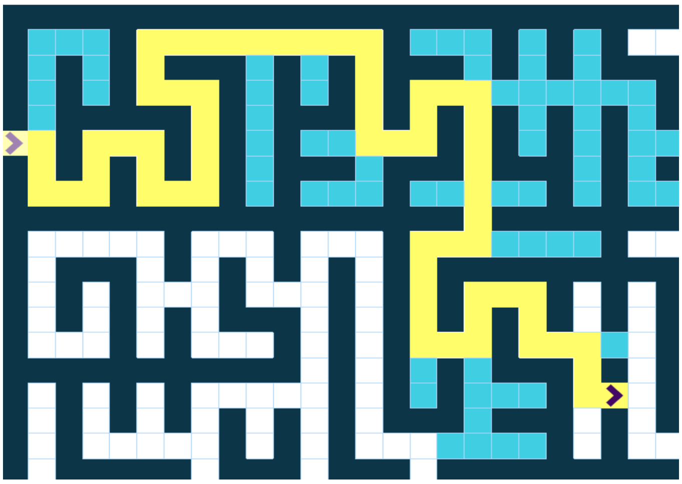


Fig 5. A* Algorithm Route Selection (Assuming User's predisposed routes have been considered)

In the above shown images, the blue nodes represent visited nodes; the yellow nodes show visited nodes/final path to destination from source node deploying the A* algorithm. This is a simulation of the Personalized Route Selection using Machine Learning's logic; an understandable, basic representation has been shown here.

V. CONCLUSION AND FUTURE WORK

In conclusion, the improvised A*algorithm's functioning has been demonstrated. Using machine learning the user is able to have the Personalized Route Selection algorithm suggest routes based on the previous traversed routes. This creates personalized route adaptations that improves the likability of the map routing applications. The user's preferences are derived using various machine learning techniques as described above. There's immense scope to this work as it can be integrated with the contemporary map routing algorithms and bring about positive change to the user's travel experiences. More robust feature selection algorithms can be used to derive the user's preferences; in practice regression seems rudimentary.

REFERENCES

[1] X. -H. Liu, D. -G. Zhang, H. -R. Yan, Y. -y. Cui and L. Chen, "A New Algorithm of the Best Path Selection Based on Machine Learning," in IEEE Access, vol. 7, pp. 126913-126928, 2019, doi: 10.1109/ACCESS.2019.2939423.
[2] Liu, X., Zhang, D., Zhang, T. et al. Novel best path selection approach based on hybrid improved A* algorithm and reinforcement learning. Appl Intell 51, 9015–9029 (2021).

[3] Thomas Koch and Elenna Dugundji. 2020. A review of methods to model route choice behavior of bicyclists: inverse reinforcement learning in spatial context and recursive logit. In Proceedings of the 3rd ACM SIGSPATIAL International Workshop on GeoSpatial Simulation (GeoSim '20). Association for Computing Machinery, New York, NY, USA, 30–37. https://doi.org/10.1145/3423335.3428165

[4] R. Grunitzki, G. d. O. Ramos and A. L. C. Bazzan, "Individual versus Difference Rewards on Reinforcement Learning for Route Choice," 2014 Brazilian Conference on Intelligent Systems, Sao Paulo, Brazil, 2014, pp. 253-258, doi: 10.1109/BRACIS.2014.53.

[5] Bazzan, A.L.C., Klügl, F. (2008). Re-routing Agents in an Abstract Traffic Scenario. In: Zaverucha, G., da Costa, A.L. (eds) Advances in Artificial Intelligence - SBIA 2008. SBIA 2008. Lecture Notes in Computer Science(), vol 5249. Springer, Berlin, Heidelberg.

[6] Bazzan, A.L.C. Opportunities for multiagent systems and multiagent reinforcement learning in traffic control. Auton Agent Multi-Agent Syst 18, 342–375 (2009).

[7] H. Li, Q. Zhang and D. Zhao, "Deep Reinforcement Learning-Based Automatic Exploration for Navigation in Unknown Environment," in IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 6, pp. 2064-2076, June 2020,doi:10.1109/TNNLS.2019.2927869.

[8] Parisotto, E. and Salakhutdinov, R., “Neural Map: Structured Memory for Deep Reinforcement Learning”, <i>arXiv e-prints</i>, 2017. doi:10.48550/arXiv.1702.08360.

[9] Lillicrap, T. P., “Continuous control with deep reinforcement learning”, <i>arXiv e-prints</i>, 2015. doi:10.48550/arXiv.1509.02971.

[10] F. Zong, M. Zeng, W. Zhong and F. Lu, "Hybrid Path Selection Modeling by Considering Habits and Traffic Conditions," in IEEE Access, vol. 7, pp. 43781-43794, 2019, doi: 10.1109/ACCESS.2019.2907725.

[11] Yisheng, Lv & Duan, Yanjie & Kang, Wenwen & Li, Zhengxi. (2014). Traffic Flow Prediction With Big Data: A Deep Learning Approach. IEEE Transactions on Intelligent Transportation Systems. 16. 865-873. 10.1109/TITS.2014.2345663.

[12] Q. Xu, J. Wang and B. Xiao, "Personalized location recommendation for location-based social networks," 2017 IEEE/CIC International Conference on Communications in China (ICCC), Qingdao, China, 2017, pp. 1-6, doi: 10.1109/ICCChina.2017.8330459.

[13] K.-B. Lee, M. A. Ahmed, D.-K. Kang, and Y.-C. Kim, “Deep Reinforcement Learning Based Optimal Route and Charging Station Selection,” Energies, vol. 13, no. 23, p. 6255, Nov. 2020, doi: 10.3390/en13236255.

[14] Siripanpornchana, Chaiyaphum & Panichpapiboon, Sooksan & Chaovalit, Pimwadee. (2016). Travel-time prediction with deep learning. 1859-1862. 10.1109/TENCON.2016.7848343.

[15] Zhang, Yue & Malikopoulos, Andreas & Cassandras, C.G.. (2015). Optimal Control and Coordination of Connected and Automated Vehicles at Urban Traffic Intersections.

[16] Hu, G., Qin, Y. & Shao, J. Personalized travel route recommendation from multi-source social media data. Multimed Tools Appl 79, 33365–33380 (2020). https://doi.org/10.1007/s11042-018-6776-9

[17] Wang, Z., Ding, W., Wang, H. (2021). A Hybrid Deep Learning Approach for Traffic Flow Prediction in Highway Domain. In: Gao, H., Wang, X., Iqbal, M., Yin, Y., Yin, J., Gu, N. (eds) Collaborative Computing: Networking, Applications and Worksharing. CollaborateCom 2020. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 350. Springer, Cham.

[18] Faiza Gul, Wan Rahiman & Syed Sahal Nazli Alhady | Kun Chen (Reviewing editor) (2019) A comprehensive study for robot navigation techniques, Cogent Engineering, 6:1, DOI: 10.1080/23311916.2019.1632046

[19] Patel, P., Narmawala, Z., Thakkar, A. (2019). A Survey on Intelligent Transportation System Using Internet of Things. In: Shetty, N., Patnaik, L., Nagaraj, H., Hamsavath, P., Nalini, N. (eds) Emerging Research in Computing, Information, Communication and Applications. Advances in Intelligent Systems and Computing, vol 882. Springer, Singapore. https://doi.org/10.1007/978-981-13-5953-8_20

[20] Tai, L., Liu, M. Mobile robots exploration through cnn-based reinforcement learning. Robot. Biomim. 3, 24 (2016). https://doi.org/10.1186/s40638-016-0055-x

[21] D. Zhao, Y. Chen and L. Lv, "Deep Reinforcement Learning With Visual Attention for Vehicle Classification," in IEEE Transactions on Cognitive and Developmental Systems, vol. 9, no. 4, pp. 356-367, Dec. 2017, doi: 10.1109/TCDS.2016.2614675.

[22] https://brilliant.org/wiki/a-star-search/?quiz=a-star-search

[23] Pathfinding Visualizer (clementmihailescu.github.io)

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.379

doi crossref

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

निस्केयर NISCAIR

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details