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ORIGINAL RESEARCH

A Comparative Analysis Between Proposed Neuro-fuzzy, Fuzzy, and Heuristic-Neuro-fuzzy Controller for Autonomous Vehicle Parking in the Dynamic Environment

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Abstract
The single-stage control is generally used to solve the autonomous parking system for dynamic environment. Sometimes, environment provides conflicting information to sensors where the single control mechanism may not be able to take prompt action. This situation causes a multiple-choice overload problem in which a single-stage system becomes confused when many decisions can be true, which can lead to collision in exceptional situations. This paper proposes a multi-stage neuro-fuzzy architecture for autonomous parallel parking in the unknown and dynamic environment. It generates an obstacle avoidance capability for the vehicle during the parking process. The multiple-choice overload problem is addressed, and a possible solution is provided by aiding a trained neural network as a pre-controller to the main fuzzy controller. The simulations results in the presence of static and moving obstacle are provided and compared with the earlier methods to prove the validity of the proposed architecture.

Keywords Autonomous parallel parking · Control system design · Neuro-fuzzy · Dynamic environment

Introduction

Online sensor-based autonomous parking through a car-like-mobile robot (CLMR) has been addressed in the earlier literatures. Parking involves two major tasks: path planning and path control. Online parking is a type of path planning where the path from start to goal is planned while motion using the sensor information. Path control is a part of the system which gives the vehicle actuator direction to move along the path. It requires a proper control system to take care of the control parameters of the vehicle (i.e., speed and steering angle). In the literature, different control system based like reactive control [1], fuzzy control [2–10], neuro-fuzzy [11], model predictive control [12, 13], sliding mode control [14, 15], and reinforcement control [16]. Among them, fuzzy control theory provides better bridge to transfer expert knowledge into machine intelligence. For perception, these approaches used multiple types of sensors like ultrasonic sensor [1, 8, 10, 13], infrared sensor [3, 7], sonar [11], laser [12], vision or camera sensor [5, 6, 9, 14–16], and fusion of such sensors [4]. Environmental variables, algorithm complexity, and processing resource available can influence sensor selection for autonomous vehicles [17].

Current challenges remain in the field of autonomous parking is a real-time planning in complex and dynamic environment where the vehicle does not have any priory information to act upon. Such challenges are widely addressed in the domain of mobile robot navigation. The primary goal of reactive navigation is to reach to the destination with collision-free path. Many reactive behavior-based control architecture using fuzzy logic theory [18–25], heuristic neural/fuzzy [26, 27], vision-based [28, 29], and LIDAR-based [30] was found in the literature. Although huge research is available for navigation, fully integrated navigation and obstacle avoidance in the existing autonomous parking architectures is very seldom used. A collision-free algorithm compatible parking system is very essential

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[31, 32] for safe and reliable path planning in the presence of dynamic environment.

The system developed in earlier study [33] comprised of a multi-level fuzzy system for an autonomous parallel parking in dynamic and unstructured environment. It includes a dedicated parallel parking controller, an obstacle avoidance controller, and a decision controller that controls the motion of the vehicle for parking. The vehicle was equipped with 12 ultrasonic sensors to collect the obstacle information from the surroundings. The system logic is developed such a way that when the vehicle sensors detect obstacle it halts temporary parking algorithm and detours the vehicle safely away from the obstacle using obstacle avoidance algorithm. When the obstacle is passed, it continues its parking. The algorithm was optimal in the sense that it can perform various functionality such as wall following, obstacle avoidance, and target steer as and when required.

The system given in [33] could improve all state-of-art architectures of online parallel parking in terms of handling dynamic environment. However, in few moments, the vehicle was finding a difficulty in coming out of obstacles. After decomposing its task very carefully, it was observed that the environment imparted different and conflicting information to the system. In this case, the single-stage obstacle avoidance algorithm was unable to make the optimum judgment, resulting in a collision. This necessitates the use of a secondary controller when the primary controller becomes dizzy for a brief period of time. A few seconds of lapse in judgment by any controller might lead to a vehicle entering a danger zone when a sudden turn or stop is required. Any stable controller design's usual functioning is not designed for such jerky movement. It can be viewed as a constraint of a single control system, and the auxiliary system aids in overcoming the constraint. This paper addresses the problem of decision-making for a single-stage obstacle avoidance system and proposes a two-stage neuro-fuzzy obstacle avoidance system along with the parking controller. It contributes a better and improved version of a multi-level parking architecture for a dynamic environment. The simulation results compare the neuro-fuzzy architecture with two other systems to prove the efficacy.

Rest of the paper is organized as follows: the section "Decision-Making Delay in Choice Overload Situation" describes the problem statement in case of single-stage control system. The section "Multi-stage Neuro-fuzzy System for Parallel Parking in the Dynamic Environment" introduces proposed work of multi-stage control system. Simulation results and discussion for the proposed system is done in the section "Simulation Results and Comparison". Finally, the paper concludes in the section "Conclusion".

Decision-Making Delay in Choice Overload Situation

On the roadways, it is common to observe expert drivers failing to drive and colliding in rare circumstances when another vehicle or obstruction is approaching at an angle to the vehicle axis. From the driver's standpoint, the fundamental reason for this is that the human mind becomes confused when the vehicle's front is obstructed and two other sides (left and right) are open. When there is multiple way, sometimes little delay in decision-making results into larger dents like collision and accidents. When such human intelligence-based autonomous machine is learned and designed, they tend to have similar behavior. Although, clear instructions are written for machines, in case of systems like fuzzy control theory, multiple rules tend to conflict between each other, and an easy and clear decision does not arrive. This happen only at certain and few occurrences, but the inherent issue cannot be neglected by the designer. A pictorial representation of decision-making delay during multiple choices is shown in Fig. 1. When two side sensors mounted on the vehicle detects open path and the reference heading angle shows no change (zero), the vehicle confuses on which side it should move.

As a general solution, if an experienced driver or machine is given an assistive signal or decision support when they arrive at this situation the decision-making process can be improved. During design process of control system, such decision support system can be included as prior to the primary control system and can be made as a multi-stage control system, as shown in Fig. 2. An idea is to add a neural network prior to the primary control system designed using a neural, a fuzzy, or any heuristic-based systems. It acts a secondary control system and give a reference and clear direction to the primary control system in cases of conflicts. The neural network is given similar learning compared to the primary control system. That

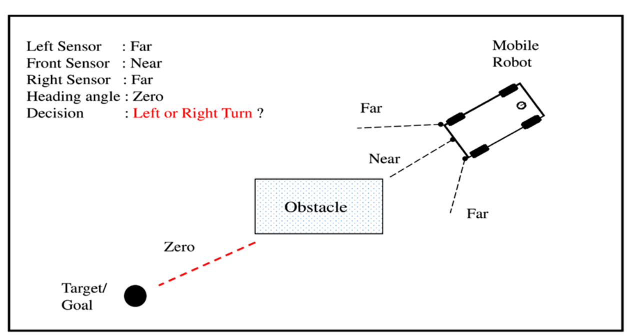

Fig. 1 Illustration of multiple-choice decision-making problem

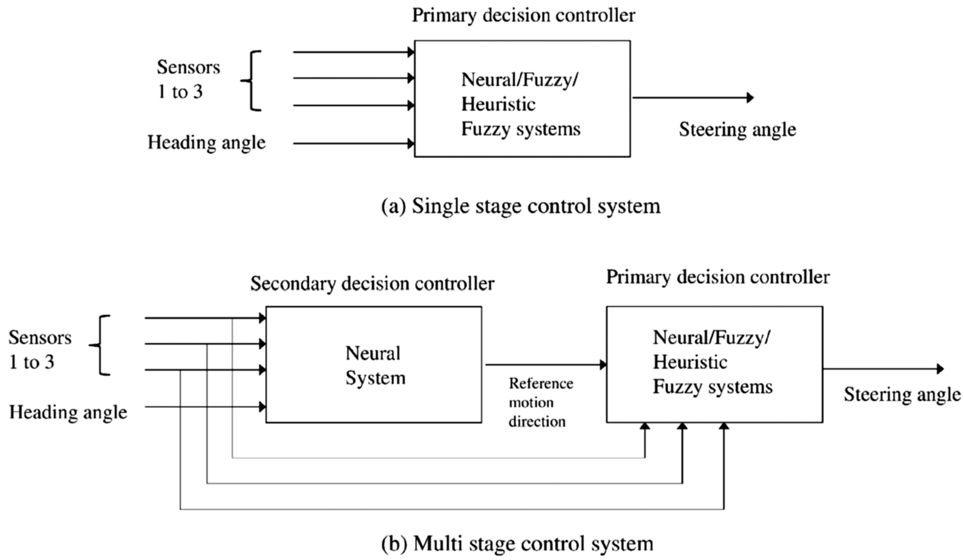

Fig. 2 **a** Single-stage and **b** multi-stage control system

means the system are capable enough to take individual decision for motion planning, but here they work in cohesive manner.

Multi-stage Neuro-fuzzy System for Parallel Parking in the Dynamic Environment

In a work by N. Nakrani and M. Joshi [33], a multi-level fuzzy system-based architecture was developed for autonomous parallel parking in dynamic environment. In that design, human-like intelligence was integrated into fuzzy-based obstacle avoidance module. The obstacle avoidance is carried out based on 81 discrete-sampled rules based on various sensor and heading angle inferences. The system was learned to give a clear left turn when the three-side sensors, right, front and left arrives at far, near, and far distances, respectively, and heading angle becomes zero. Even though during certain events, the system fails to avoid a collision that will be seen in later part of the simulation results. As an improvement to that architecture, a multi-stage neuro-fuzzy-based architecture is proposed in this paper. A neuro-fuzzy architecture for obstacle avoiding parallel parking is shown in Fig. 3. The original architecture is derived from [33] and modified into multi-stage control system architecture. An addition of a neural network in the system is shown by red-colored box. It will act as a secondary control system and will help in decision-making process by obstacle avoidance controller referred to fuzzy logic controller 2 (FLC_2), as shown in Fig. 3. The detail design of all individual blocks

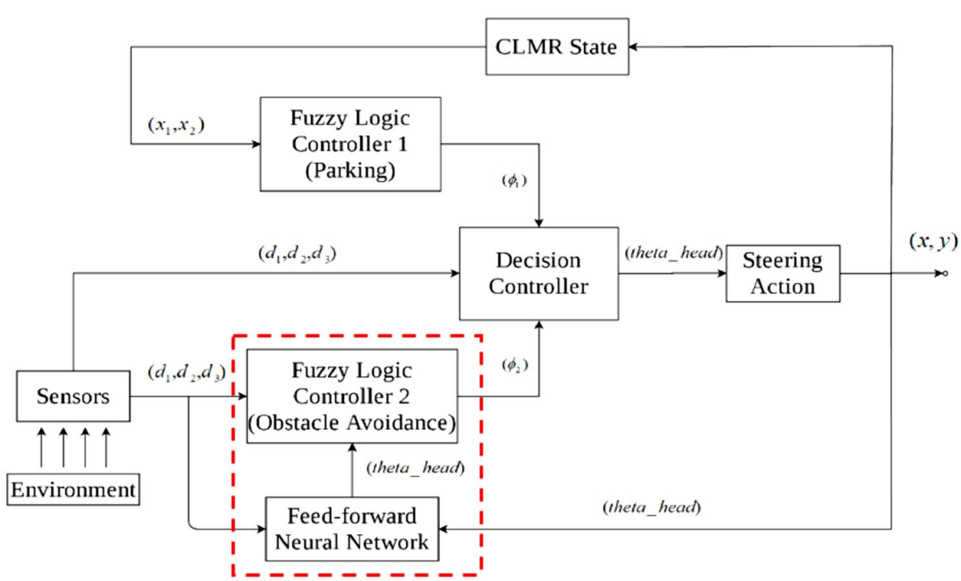

Fig. 3 A Neuro-Fuzzy architecture for parallel parking in dynamic environment

and entire working flow of architecture is given in [33], and it is not included in this paper to keep the context of this paper very specific.

A. Training of neural network for hybrid neuro-fuzzy system

The overall architecture shown in Fig. 3 is designed for an autonomous vehicle parallel parking in dynamic environment where the vehicle is assumed to be equipped with ultrasonic sensors and three-side information is given to the system for online path planning as d_1, d_2, and d_3. Another input is a heading angle (referred as, *theta_head*) that gives the information of long-term aim of reaching the goal.

The feed-forward neural network is also designed and trained with the same set of inputs and outputs given to the obstacle avoidance controller (FLC_2). It is used to compute the reference heading angle before the actual obstacle avoidance fuzzy controller. A neural network is created with two hidden later back-propagation architecture. It is trained with the datasets generated from the FLC_2. As the system takes the actual value as an input, the datasets are generated with the help of interpolation. A few samples of training set data are given in Table 1. The output of the neural network is an upgraded heading angle (*new_theta_head*) that is feed into the FLC_2 and acts as an input for the FLC_2.

Neural network training aimed to give the inference of heading angle for the fuzzy system. Hence, the neural network is trained for significance rather than accuracy. It is trained with different 3773 training pairs generated from the range of its inputs. For the sensor groups, the range is from [0, 6] meters, and for the reference theta_head, the range is from [− 45° to + 45°]. All actual values were normalized and trained up to 10,000 epochs. The training function used was 'trainlm, and the learning function used was 'learngdm'. Two hidden layers with 30 and 20 neurons in the first and second hidden layers were generated in nntool. Mean square error was used as a performance function. The trained network has 790 learning parameters, and the training pairs-to-learning parameter ratio was kept as 4.77. The network was trained until the performance function was achieved to a significantly lower value. The conventional feed-forward back-propagation network was used to update the weights.

Simulation Results and Comparison

The validation of neuro-fuzzy architecture for parallel parking is given with the simulation results and comparison to the earlier approaches. For simulation results, parallel parking environment with the static and moving obstacle is created in MATLAB software. A dynamic environment of 16-by-16 m is created with car-like mobile robot (CLMR) and parking slot. The CLMR is taken as a non-holonomic rectangle shape with the dimension matching to the Hyundai i20 car. Parking length is taken as 1.5 times the vehicle's length, and width is taken as 2.2 times the width of the vehicle that matches some of the western country standards. The CLMR length is taken as 4 m, and the width is taken as 1.8 m. The speed of the vehicle is taken as 1 m per second and the speed of the moving obstacle is regarded lower than the vehicle.

The proposed design in this paper is compared with a fuzzy architecture [33] and a heuristic-neuro-fuzzy reactive navigation given in [27]. The simulations are tested and compared to a similar environment with the same set of parameters. A heuristic-neuro-fuzzy reactive navigation given in [27] has described nine different obstacle avoidance classes, as shown in Fig. 4, and relevant fuzzy rules for each class. They used 80 sampled heuristic rules for reactive navigation. To compare their navigation rules in proposed parking system [33], obstacle avoidance controller (FLC_2) has been replaced with 81 discrete rules to their 80 rule-base controller. All the three systems (a fuzzy, a proposed neuro-fuzzy, and a heuristic neuro-fuzzy) are evaluated quantitatively in terms of (a) minimum safe distance with nearby obstacles (MIN_OBS_DIST), (b) minimum no of steps to reach the parking goal coordinates (TOTAL STEPS), or (c) the minimum number of collisions. Out of all experiments performed, a few selected cases are presented for moving and static environments.

Table 1 Sampled rules used to train the neural network

If					Then
Rule no	Left Obs (d_1 value)	Front Obs (d_2 value)	Right Obs (d_3 value)	Old_theta_head	New_theta_head
1	Far (4)	Far (4)	Far (4)	N (− 25°)	NB (− 43.5°)
2	Far (4)	Far (4)	Far (4)	Z (0°)	ZE (0°)
3	Far (4)	Far (4)	Far (4)	P (+ 25°)	PB (+ 43.5°)
4	Near (1)	Near (1)	Far (4)	N (− 25°)	PB (+ 43.5°)
5	Far (4)	Far (4)	Near (1)	P (+ 25°)	ZE (0°)

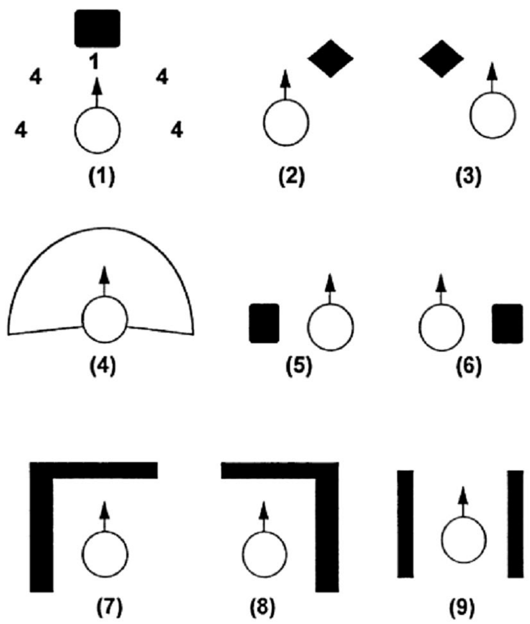

Fig. 4 Different obstacle avoidance classes as given in [27]

Figure 5 shows the continuous step sequence of three different scenarios for the moving obstacles. The first and the second rows stand for a case where the moving obstacle is coming toward the CLMR. The third row is a case where the moving obstacle is moving away from the CLMR, and the CLMR is trying to overtake the obstacle. Figure 5a, d, and g shows the simulations for the proposed fuzzy system. Figure 5b, e, and h shows the simulations for this paper's proposed neuro-fuzzy system. It is to be noted that the results for the neuro-fuzzy system are mostly similar in all cases, except the few ones that will be discussed later. Figure 5c, f, and i shows the simulations for a heuristic-neuro-fuzzy provided in [27]. This system gives a collision in the second case, as shown in Fig. 5f.

Similarly, a few more scenarios with the presence of a static obstacle are used, as shown in Fig. 6, for the comparison between three different systems. It can be noted that a collision occurs in both cases while running with the heuristic-neuro-fuzzy system by [27], as shown in Fig. 6c and f.

To show the impact of adding a neural network in the proposed system, we have simulated two different cases out of many, where the conflicting situation is present for a single-stage fuzzy system, and it fails. Figure 7 shows a scenario of parallel parking where static obstacle and initial position of CLMR is placed in such a way that when CLMR approaches to the corner of the obstacle its two sides left and right is open, while the front side shows an obstacle. This instance is conflicting for fuzzy, because multiple rules become valid, and sometimes, such a fraction of delay may lead to a collision. However, in the same scenario, when the two-stage neuro-fuzzy system is used, CLMR completely avoids collision with an obstacle and achieves parking. In this case, when the conflicting instance arrives, the output of the neural network gives a proper and single judgment for the fuzzy system. Hence, it provides better tuning of the overall system. Figure 7b provides the results for the proposed neuro-fuzzy system, and Fig. 7c provides the results for the heuristic-neuro-fuzzy [27]. Here, both the multi-stage system avoids the collision compared to the single-stage fuzzy system.

Another scenario is shown in Fig. 8, where the neuro-fuzzy system gives better performance compared to the fuzzy system and the heuristic-neuro-fuzzy design. These cases are only a few cases where the fuzzy system may struggle at a certain instant. Therefore, with this modified system, it can be said that a few chances of collision also may prevent with architecture presented in [33].

The performance evaluation of all three systems is given in Table 2. They are compared using quantitative parameters as TOTAL STEPS—indicating total path traversed and MIN_OBS_DIST—indicating minimum safety margin observed by CLMR during its path, and COLLISION DETECTED-indicator of safe operation. Let us try to evaluate performance in some cases. For example, in case 1, TOTAL STEPS taken by CLMR for maneuvering from START to END are the same. This indicates that total path traversing time is the same in all algorithms. In addition, all algorithms can execute performance safely as COLLISION DETECTED is "No" in all cases. However, it is to be noted that the minimum obstacle distance (MIN_OBS_DIST) measured from any sensor is lesser in the proposed NF-based design, pointing out that the proposed NF-based design provides higher safety of margin than other algorithms in the same situations.

Similarly, in case 2, the heuristic-fuzzy-based system would fail to park the vehicle with safety, the fuzzy-based system would park it with the shortest distance, and minimum safety distance is better with the proposed NF-based parking algorithm at slightly more cost the important point is it avoids the collision in situations when the heuristic-fuzzy fails. The fuzzy-based system fails to perform collision-free parking in case 6 and case7. In case 6, heuristic-based algorithm performs best. This may be due to that system was trained better for those environmental conditions. But that cannot be generalized as the same heuristic-based algorithm fails to give a safe paring solution in cases 2, 4, 5, and 7. It can be concluded that the fuzzy heuristic system is not much

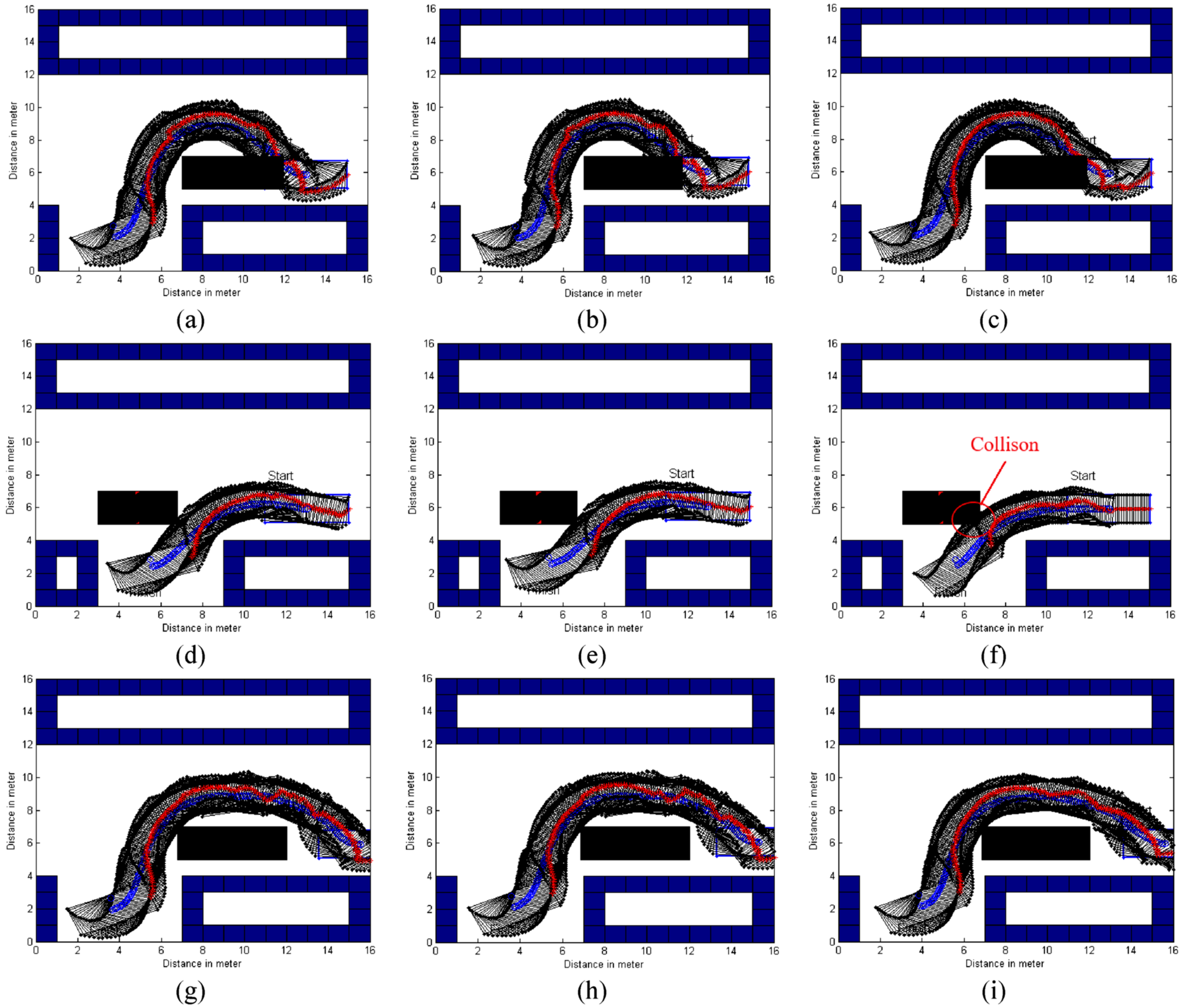

Fig. 5 Results in the presence of moving obstacle in **a** Case 1: fuzzy system. **b** Case 1: neuro-fuzzy system. **c** Case 1: heuristic system [27]. **d** Case 2: fuzzy system. **e** Case 2: neuro-fuzzy system. **f** Case 2: heuristic system [27]. **g** Case 3: fuzzy system. **h** Case 3: neuro-fuzzy system. **i** Case 3: heuristic system [27]

reliable in general. In Case 7, when both heuristics fuzzy and fuzzy systems fail, only an NF-based system can give a safer and optimal solution; quantitative performance evaluation of different algorithms for different environmental scenario. In Table 2, all the failed case scenarios with its respective algorithms highlighted in bold text in last two columns.

Conclusion

From the simulation results and comparison provided in previous section, it can be concluded that performances of fuzzy and proposed neuro-fuzzy systems are almost comparable, and they both outperform the heuristic-neuro-fuzzy-based approach, and the proposed NF-based system is behaviourally optimal, which balances well between shortest path and safety of operation succeeds in most dynamic environment classes.

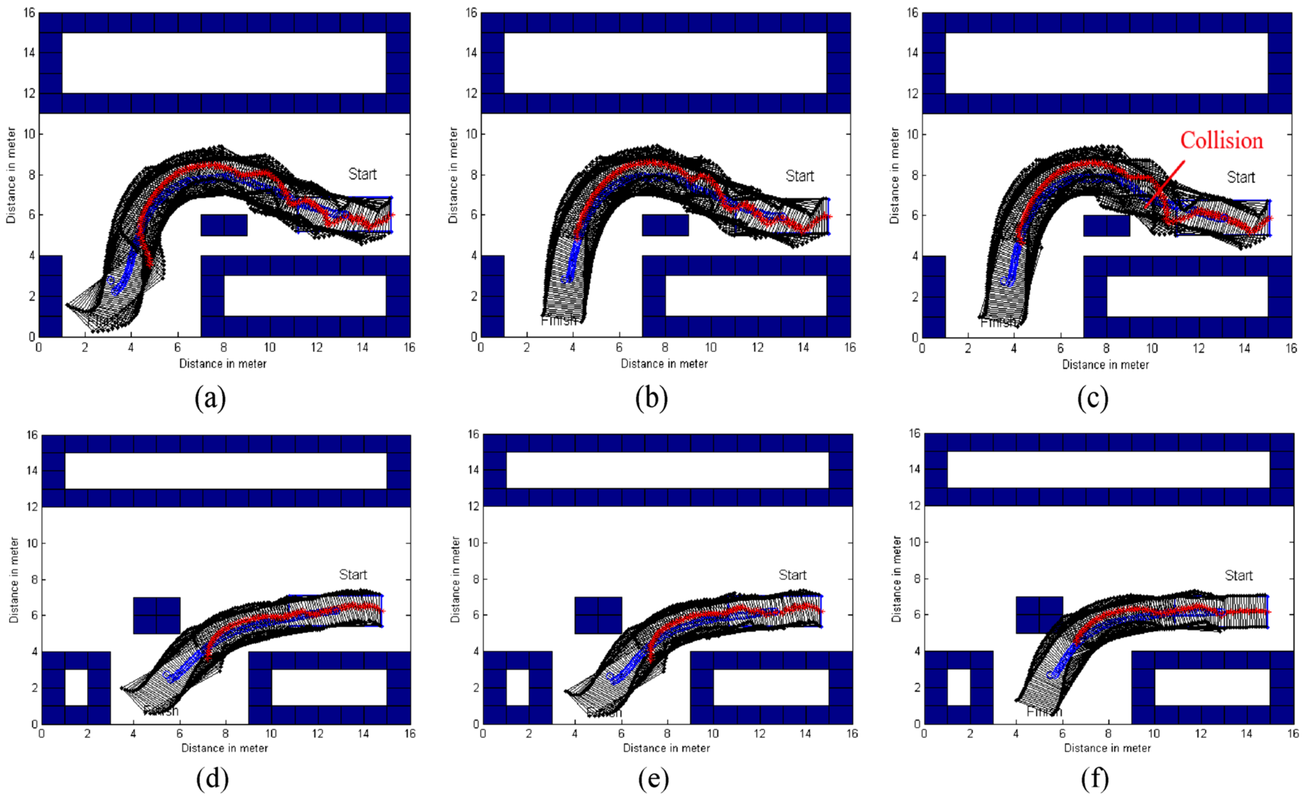

Fig. 6 Results in the presence of a static obstacle in **a** Case 4: fuzzy system. **b** Case 4: neuro-fuzzy system. **c** Case 4: heuristic system [27]. **d** Case 5: fuzzy system. **e** Case 5: neuro-fuzzy system. **f** Case 5: heuristic system [27]

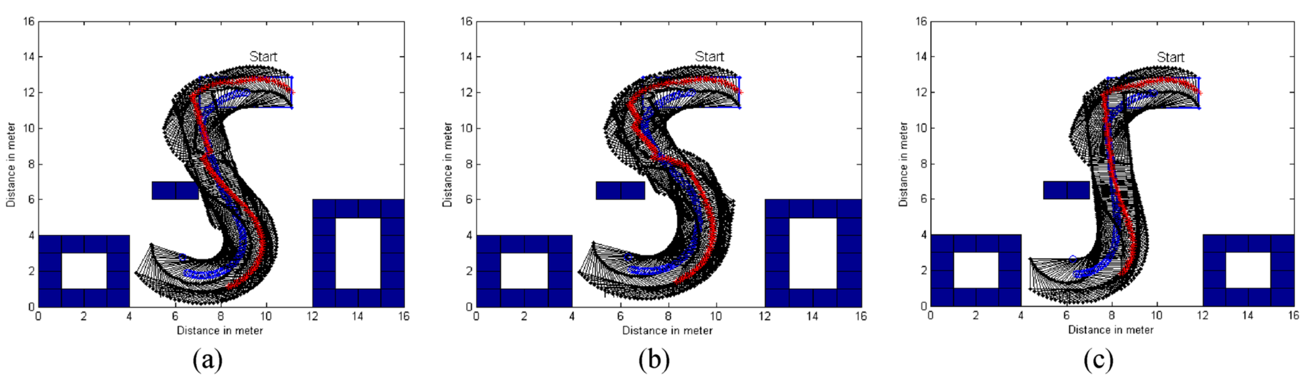

Fig. 7 Case 6: **a** A fuzzy system, **b** a neuro-fuzzy system, and **c** a heuristic-neuro-fuzzy in a typical scenario of static obstacle present in the path of parking

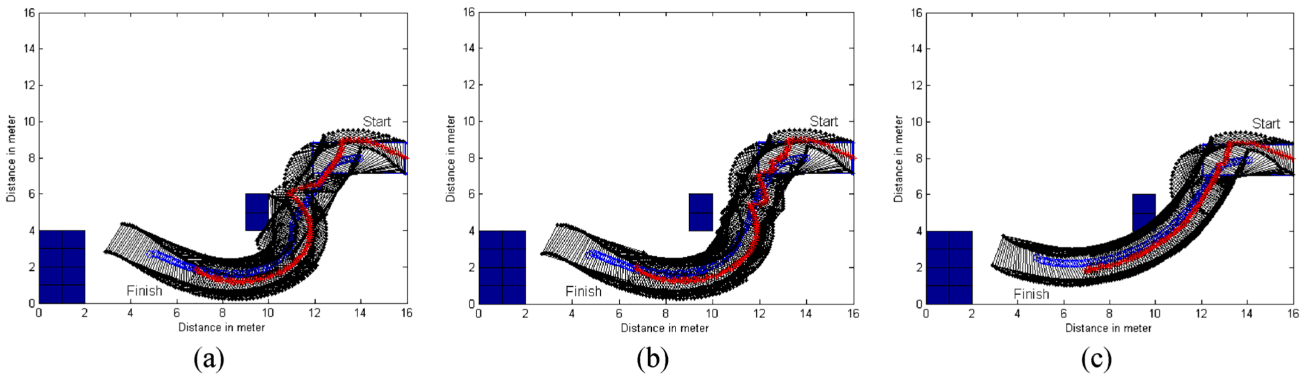

Fig. 8 Case 7: **a** a fuzzy system, **b** a neuro-fuzzy system, and **c** a heuristic-neuro-fuzzy in a typical scenario of static obstacle present in the path of parking

Table 2 Quantitative performance evaluation of Fuzzy [33], proposed neuro-fuzzy, and heuristics NF [27] algorithms for different environmental scenario

Case	Type of obstacle	Name of algorithm	Total steps	MIN_OBS_DIST	Collision detected?
1	Moving	Fuzzy	146	0.4813	No
		Proposed neuro-fuzzy	146	0.5152	No
		Heuristic NF	146	0.2525	No
2	Moving	Fuzzy	86	0.4664	No
		Proposed neuro-fuzzy	89	0.5014	No
		Heuristic NF	87	**0**	**Yes**
3	Moving	Fuzzy	170	0.8058	No
		Proposed neuro-fuzzy	165	0.5837	No
		Heuristic NF	165	0.7026	No
4	Static	Fuzzy	127	0.4234	No
		Proposed neuro-fuzzy	129	0.4511	No
		Heuristic NF	127	**0**	**Yes**
5	Static	Fuzzy	84	0.1694	No
		Proposed neuro-fuzzy	84	0.2302	No
		Heuristic NF	87	**0**	**Yes**
6	Static	Fuzzy	130	**0**	**Yes**
		Proposed neuro-fuzzy	132	0.2615	No
		Heuristic NF	122	0.06	No
7	Static	Fuzzy	142	**0**	**Yes**
		Proposed neuro-fuzzy	143	0.2836	No
		Heuristic NF	115	**0**	**Yes**

Declarations

Conflict of interest All authors declare that they have no conflicts of interest.

References

1. Paromtchik IE, Laugier C. Autonomous parallel parking of a nonholonomic vehicle. Proc Conf Intell Veh. 1996. https://doi.org/10.1109/IVS.1996.566343.
2. Gómez-Bravo F, Cuesta F, Ollero A. Parallel and diagonal parking in nonholonomic autonomous vehicles. Eng Appl Artif Intell. 2001;14(4):419–34. https://doi.org/10.1016/S0952-1976(01)00004-5.
3. Chang SJ, Li THS. Design and implementation of fuzzy parallel-parking control for a car-type mobile robot. J Intell Robot Syst Theory Appl. 2002;34(2):175–94. https://doi.org/10.1023/A:1015664327686.
4. Zhao Y, Collins EG. Robust automatic parallel parking in tight spaces via fuzzy logic. Rob Auton Syst. 2005;51(2–3):111–27. https://doi.org/10.1016/j.robot.2005.01.002.
5. Chao CH, Ho CH, Lin SH, Li THS. Omni-directional vision-based parallel-parking control design for car-like mobile robot. IEEE Int Conf Mechatron. 2005. https://doi.org/10.1109/ICMECH.2005.1529319.
6. Wang WC, Chen R. A vision-based fuzzy logic controller for backing-up an autonomous vehicle. J Intell Fuzzy Syst. 2008;19(4–5):273–84.
7. Panomruttanarug B, Higuchi K. Fuzzy logic based autonomous parallel parking system with Kalman filtering. SICE J Control Meas Syst Integr. 2010;3(4):266–71. https://doi.org/10.9746/jcmsi.3.266.
8. Li THS, Yeh YC, Da Wu J, Hsiao MY, Chen CY. Multifunctional intelligent autonomous parking controllers for carlike mobile robots. IEEE Trans Ind Electron. 2010;57(5):1687–700. https://doi.org/10.1109/TIE.2009.2033093.
9. Aye YY, Watanabe K, Maeyama S, Nagai I. Design of an image-based fuzzy controller for autonomous parking of four-wheeled mobile robots. Int J Appl Electromagn Mech. 2016;52(3–4):859–65. https://doi.org/10.3233/JAE-162180.
10. Huang S-J, Hsu Y-S. Parking space detection and trajectory tracking control for vehicle auto-parking. Int J Mech Mechatron Eng. 2017;11(10):1712–8.
11. Demirli K, Khoshnejad M. Autonomous parallel parking of a car-like mobile robot by a neuro-fuzzy sensor-based controller. Fuzzy Sets Syst. 2009;160(19):2876–91. https://doi.org/10.1016/j.fss.2009.01.019.
12. Song J, Zhang W, Wu X, Cao H, Gao Q, Luo S. Laser-based SLAM automatic parallel parking path planning and tracking for passenger vehicle. IET Intell Transp Syst. 2019;13(10):1557–68. https://doi.org/10.1049/iet-its.2019.0049.
13. Ye H, Jiang H, Ma S, Tang B, Wahab L. Linear model predictive control of automatic parking path tracking with soft constraints. Int J Adv Robot Syst. 2019;16(3):1–13. https://doi.org/10.1177/1729881419852201.
14. Du X, Tan KK, Htet KKK. Autonomous reverse parking system-vision approach through ridge detector and Kalman filter. Int J Mechatronics Autom. 2015;5(1):22–33. https://doi.org/10.1504/IJMA.2015.068450.
15. Du X, Tan KK. Autonomous reverse parking system based on robust path generation and improved sliding mode control. IEEE Trans Intell Transp Syst. 2015;16(3):1225–37. https://doi.org/10.1109/TITS.2014.2354423.
16. Zhang P, et al. Reinforcement learning-based end-to-end parking for automatic parking system. Sensors (Switzerland). 2019. https://doi.org/10.3390/s19183996.
17. Van Brummelen J, O'Brien M, Gruyer D, Najjaran H. Autonomous vehicle perception: The technology of today and tomorrow. Transp Res Part C Emerg Technol. 2018;89:384–406. https://doi.org/10.1016/j.trc.2018.02.012.
18. Li W. Fuzzy-logic-based reactive behavior control of an autonomous mobile system in unknown environments. Eng Appl Artif Intell. 1994;7(5):521–31. https://doi.org/10.1016/0952-1976(94)90031-0.
19. Joshi MM, Zaveri MA. Fuzzy based autonomous robot navigation system. Proc INDICON IEEE India Counc Conf. 2009. https://doi.org/10.1109/INDCON.2009.5409419.
20. Dongshu W, Yusheng Z, Wenjie S. Behavior-based hierarchical fuzzy control for mobile robot navigation in dynamic environment. Proc Chin Control Decis Conf. 2011. https://doi.org/10.1109/CCDC.2011.5968614.
21. Motlagh O, Tang SH, Ismail N, Ramli AR. An expert fuzzy cognitive map for reactive navigation of mobile robots. Fuzzy Sets Syst. 2012;201:105–21. https://doi.org/10.1016/j.fss.2011.12.013.
22. Mo H, Tang Q, Meng L. Behavior-based fuzzy control for mobile robot navigation. Math Probl Eng. 2013. https://doi.org/10.1155/2013/561451.
23. Mohanty PK, Parhi DR. Navigation of autonomous mobile robot using adaptive network based fuzzy inference system. J Mech Sci Technol. 2014;28(7):2861–8. https://doi.org/10.1007/s12206-014-0640-2.
24. Omrane H, Masmoudi MS, Masmoudi M. Fuzzy logic based control for autonomous mobile robot navigation. Comput Intell Neurosci. 2016. https://doi.org/10.1155/2016/9548482.
25. Fathinezhad F, Derhami V, Rezaeian M. Supervised fuzzy reinforcement learning for robot navigation. Appl Soft Comput J. 2016;40:33–41. https://doi.org/10.1016/j.asoc.2015.11.030.
26. Xu WL, Tso SK. Sensor-based fuzzy reactive navigation of a mobile robot through local target switching. IEEE Trans Syst Man Cybern Part C. 1999;29(3):451–9. https://doi.org/10.1109/5326.777079.
27. Song KT, Sheen LH. Heuristic fuzzy-neuro network and its application to reactive navigation of a mobile robot. Fuzzy Sets Syst. 2000;110(3):331–40. https://doi.org/10.1016/S0165-0114(97)00401-6.
28. Antonelli G, Chiaverini S, Fusco G. A fuzzy-logic-based approach for mobile robot path tracking. IEEE Trans Fuzzy Syst. 2007;15(2):211–21. https://doi.org/10.1109/TFUZZ.2006.879998.
29. Hwang CL, Shih CY. A distributed active-vision network-space approach for the navigation of a car-like wheeled robot. IEEE Trans Ind Electron. 2009;56(3):846–55. https://doi.org/10.1109/TIE.2008.2004388.
30. Morales N, Arnay R, Toledo J, Morell A, Acosta L. Safe and reliable navigation in crowded unstructured pedestrian areas. Eng Appl Artif Intell. 2016;49:74–87. https://doi.org/10.1016/j.engappai.2015.11.008.
31. Li B, et al. Optimization-based trajectory planning for autonomous parking with irregularly placed obstacles: a lightweight iterative framework. IEEE Trans Intell Transp Syst. 2021. https://doi.org/10.1109/TITS.2021.3109011.

32. Zhang Z, et al. A guaranteed collision-free trajectory planning method for autonomous parking. IET Intell Transp Syst. 2021;15(2):331–43. https://doi.org/10.1049/itr2.12028.
33. Nakrani NM, Joshi MM. A human-like decision intelligence for obstacle avoidance in autonomous vehicle parking. Appl Intell. 2021. https://doi.org/10.1007/s10489-021-02653-3.