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ORIGINAL RESEARCH

Analysis and design of fuzzy-based manoeuvring model for mid-vehicle collision avoidance system

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Abstract

This paper offers a fuzzy-based manoeuvring model labeled as Fuzzy-based Midvehicle Collision Avoidance System (FMCAS) resolving two road crash scenarios. The first scenario covers dual situations (a) Mid vehicle collision avoidance with the rear vehicle under no front vehicle condition and (b) Curvilinear path strategy based on real road conditions. While the suitable curvilinear motion to fit the constrained path for parallel parking is the other scenario. Curvilinear fitting strategy on the left and right sides is achieved by the mid (host) vehicle using fuzzy interpolation techniques modeled by FMCAS. Also, the offset-based curvilinear path determined by FMCAS automatically fits the constraint path to avoid vehicle crashes in highly occupied lanes. In this methodology, path constraint is applicable for both scenarios in forward and reverse directions. The appropriate constraint paths estimated using the developed fuzzy-based polynomial fitting addresses the diverse vehicle kinematic issues. Mean square error values of 3.9443×10^{-28} m and 0.0148–0.7210 m about the proposed fuzzy respect to crisp and FMCAS are also capable of delivering diverse consequents in highly intact road scenarios. The fuzzy rule base is motivated in this research article to obtain a collision-free environment addressing many collision conditions in the real-time scenario.

Keywords FMCAS · Offset-based curvilinear path · Parallel parking · Fuzzy-based polynomial fitting · Mean square error

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1 Introduction

National Transportation Safety Board (Avuthu Sai et al. 2020) frames a report deliberating a rear-end collision is mainly owing to driver distractions in real-time scenarios. Therefore, research in collision avoidance is more oriented towards handling rear-end collision. Accordingly, several maneuvering models targeting collision avoidance were presented in (Balasubramaniam et al. 2020a, b). Recently, Crisp and Fuzzy modeled adaptive collision avoidance introduced in (Biruntha et al. 2020), estimated the constraint paths through longitudinal motion analysis by considering the relative distance between adjoining vehicles. Furthermore, (Ching-Fu et al. 2014) considered the front vehicle dimension for fitting the constraint path to overcome critical situations. In (Deivendran et al. 2020), a fixed polynomial fitting strategy was adopted that neglected the dynamics of surrounding vehicles resulting in improper navigation. Owing to non-synchronization between the on-road vehicles, (Devipriya et al. 2020; Donepudi et al. 2020) integrated inter-communication schemes into their collision avoidance that was worthy for low speeds but failed miserably under high-speed conditions. These rapidly varying vehicle dynamics was considered in (Ganesh Kumar et al. 2020; Georg et al. 2014) by fusing GPS navigation systems into the collision avoidance system that escalated the computational load of the GPS base stations and also demanded to scale to compute the accurate position of the vehicle. The vision-based methods (Gowthamani et al. 2020; Helene et al. 2014; Junsoon et al. 2015) resolved the aforesaid issue but suffered majorly from the object, road cornering errors and increased the system complexity.

In conjunction with the above schemes, another polynomial fitting technique was presented in (Jagadeesh et al. 2020) that suited parallel parking applications. This system was unable to dynamically adapt a constraint path with regard to the real-time environments. Jose (2003) addressed this issue by providing curvilinear trajectories through a two-step process that assisted automatic car parking. Although seemed efficient, the path planning strategy was cumbersome owing to improper interpolation that leads to misalignment of the destination for the parking vehicle. Similarly, the fuzzy-based intelligent transportation system (Junsoon et al. 2015) employed lateral control to converge towards the desired path with multiple consequents. Further fuzzy enhancement in vehicle manoeuvring was presented in (Kanmani et al. 2020) for collision avoidance that suited only slow speed applications. This concept was further extended to rear-end collision avoidance using Vehicle-to-Infrastructure (V2I) in (Karthikeyan et al. 2020) that targeted low-speed conditions. Therefore, the research articles contributed to the intelligent transportation system addressing the longitudinal and lateral motion for the different scenarios that are cited with proper analysis.

Thus, this paper presents a fuzzy-based mid-vehicle manoeuvring model for dynamic road environments. The intended FMCAS instantaneously estimates longitudinal and lateral paths by fuzzy modeling of the diverse, dynamic parameters associated with the front, rear, and mid vehicles under rigorous road conditions. The novel membership functions evolved in this work will assist the mid vehicle to navigate in a safe road zone realized using Lagrange interpolation techniques. The presented methodology provides lateral path estimation schemes for adopting different path strategies under high-speed road conditions that ensure collision less manoeuvring.

FMCAS covers three offerings in fuzzy space that includes,

a. Adaptive longitudinal path estimation for the mid vehicle in maintaining relative distance with the rear vehicle under no front vehicle condition.
1 Fuzzy path fitting model for mid vehicle sandwiched between both ends
2 Accordingly, a suitable curvilinear motion model is introduced for real-time lane switching.

2 Intended methodology

In the automotive domain, short-range applications stress on novel collision avoidance systems to effectively handle high traffic, and the lane was switching conditions (Sathiya Kumar et al. 2020; Sudhakar et al. 2020). The recent death-proof concept of automotive technology is one such instance signaling the vision of future automotive vehicles. This latest trend enforces the intelligent navigation systems to take the appropriate path in ensuring passenger's safety and comfort under any diverse conditions of the surrounding vehicles. Apparently, this proposal conveys an intelligent path estimation scheme based on evasive manoeuvring of adjoining (front and rear) vehicles to avoid imminent situations. This intention delivers FMCAS that incorporates two fuzzy models for constraint path estimation and parallel parking (Shuwen 2011; Sudhakar 2012). Detailed explanations pertaining to the introduced fuzzy models with relevant scenarios are dealt with in subsequent sections. The intended fuzzy-model offers the solution for a typical road scenario that is portrayed in Fig. 1.

Fuzzy modeling considers the kinematics parameters that include Host vehicle velocity (V_H), Rear vehicle distance (d_r), Predefined rear distances (d_{pr}), Rear vehicle velocity ($V_{T,r}$), Front vehicle distance (d_f), Front vehicle velocity ($V_{T,f}$), Maximum (long) predefined front distance

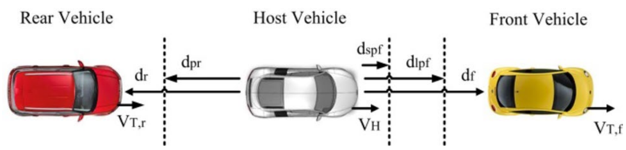

Fig. 1 Necessary parameters targeted FCAS

(d_{lpf}), Minimum (short) predefined front distance (d_{spf}). Based on Fig. 1, crisp path estimation conditions are briefed in Table 1 that are established in accordance with the adjoining vehicle kinematics (Sudhakar and Chenthur Pandian 2015).

This crisp knowledge is fuzzily transformed in this proposal so as to enhance the collision avoidance system that also embraces more collision risks. This methodology freezes the maximum front and rear distance values prescribed in (Mahdi et al. 2015; Michael et al. 2002) for short-range applications. FMCAS addresses the different crash conditions illustrated in Fig. 2 that covers No Front-End Vehicle and the presence of Front-End Vehicle with offset (Sudhakar Sengan and Chenthur Pandian 2012, 2013, 2016).

2.1 No front-end vehicle condition

In this condition, adaptive cruise control action is performed to maintain appropriate distance with the rear vehicle. Abnormal driver behavior from the rear vehicle leads to the possible imminent collision with the host vehicle. Being a simple scenario, this paves the way for the majority of rear-end collisions (Sudhakar et al. 2020a, b, c).

To sidestep such imminent collision, precise relative kinematic conditions are framed in the first two rows of Table 1 and depicted in Fig. 2a.

2.2 Front-end vehicle with offset

The constraint discussed above cannot be anticipated at all times in real-time scenarios where the roads remain fully occupied. Therefore, the front vehicle is also considered in formulating the FMCAS, as illustrated in Fig. 2 (Teawon et al. 2014; Timothy 2010; Valdes-Vela et al.

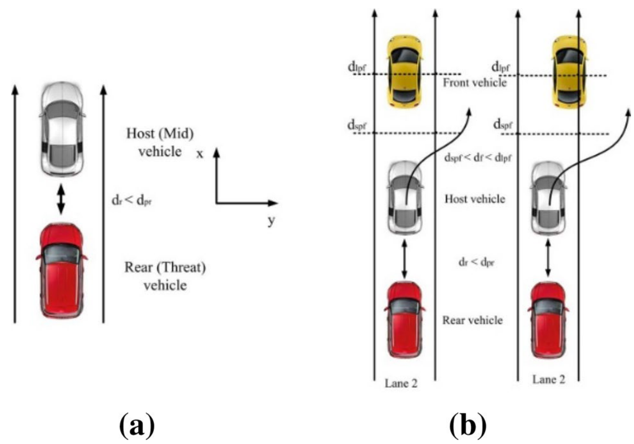

Fig. 2 **a** Imminent Collision avoidance under no front vehicle condition. **b** The curvilinear strategy of mid (host) vehicle is based on the front vehicle position

2013; Vasanthi et al. 2020). In such situations, an intelligent system seeks to offset the position of the front vehicle to estimate an appropriate path; (Vicente et al. 2012) to avoid the collision. Thus, the values of d_f, d_r and V_H are estimated that are mapped respectively against $d_{lpf,}d_{pr}$, $V_{T,f}$ and$V_{T,r}$, and if found equal, FMCAS warns the host vehicle to maintain the constant speed. In another situation, the distance parameters d_f and d_r are constrained between the maximum (long) predefined front distance (d_{lpf}), minimum (short) predefined front distance (d_{spf}), rear distance (d_{pr}) and host velocity (V_H) are bounded by $V_{T,f}$ and$V_{T,r}$. Accordingly, the host vehicle must adopt a strategy to avoid an imminent collision at the rear-end of the host vehicle, as illustrated in Fig. 2b, and the corresponding path formulations are disclosed in the third and fourth row of Table 1.

Hence, the precise model framed in Table 1 under the front vehicle condition is imprecisely controlled using FMCAS. Moreover, a fuzzy interpolation technique presented in this paper establishes the instant position of mid-vehicle for proper path estimation under different offset positions of the front vehicle.

Table 1 Conditional kinematic parameters for path estimation and Parallel Parking

Model	FV	FV distance, d_f [m]	FV velocity, $V_{T,f}$ [Km/h]	RV	RV distance, d_r [m]	RV velocity, $V_{T,r}$ [Km/h]	Mode
Path estimation	No	$> d_{lpf}$	None	Yes	$> d_{pr}$	None	No acceleration
	No	$> d_{lpf}$	None	Yes	$\leq d_{pr}$	$> V_H$	Acceleration
	Yes	$= d_{lpf}$	$= V_H$	Yes	$= d_{pr}$	$= V_H$	Warning
	Yes	Between $d_{lpf}$and d_{spf}	$\leq V_H$	Yes	$< d_{pr}$	$> V_H$	CCM (FD)
Parallel Parking	None	None	None	None	None	None	CCM (RD)

2.3 Parallel parking scenario

In the Parallel Parking application, the curvilinear motion model is fitted to reverse path, as depicted in Fig. 3, which deliberates the direction of the motion of the host vehicle.

As evident in Fig. 3, the host vehicle (parking) is expected to be steered in the free slot available between the parked vehicles. Depending on the offset position of the parking vehicle, a constraint path, as highlighted with a downward curve, is fitted by FMCAS (Vijaya Kumar et al. 2020).

3 FMCAS model

The above-listed scenarios clearly signify the need for automotive navigation models with the potential for addressing intricate road conditions. To perform such navigation, the ESR system from Delphi in (Won 2005; Xiang et al. 2014; Wang et al. 2015) evaluates the distance (d) and velocity of target(front and rear) vehicles from range (R), speed of signal (c), delay time (τ), target coordinates (x,y), target angle (φ), sensor coordinates (x_s,y_s), carrier frequency (f_c), and Doppler frequency (f_D) received frequency (f_r), transmitted frequency(f_t) using Eqs. (1)–(7). where V_H represents host vehicle velocity and V_R is the relative velocity between the host and the target vehicle.

$$R = \frac{c\tau}{2} \tag{1}$$

$$x_s = R\cos\varphi \tag{2}$$

$$y_s = R\sin\varphi \tag{3}$$

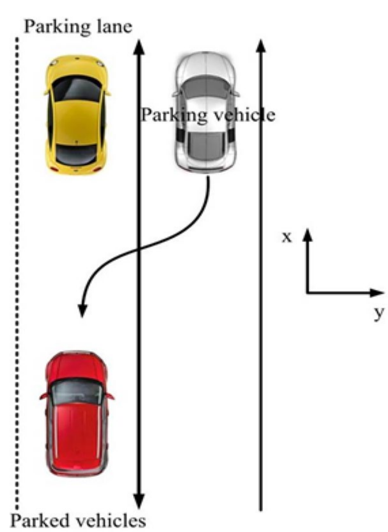

Fig. 3 Curvilinear trajectory model for parking vehicle

$$d = \sqrt{\left(x - x_s\right)^2 + (y - y_s)^2} \tag{4}$$

$$V_R = \frac{cf_D}{2f_c} \tag{5}$$

$$f_D = f_r - f_t \tag{6}$$

$$V_T = V_H + V_R \tag{7}$$

However, to encounter the rapidly varying road scenarios, FMCAS (Murugan et al. 2020a, b; Petrov and Nashashibi 2014) involves a Mamdani type Fuzzy Interference System that renders diverse consequences and swift adaptation. This functionality is mainly realized for the curvilinear model through a novel membership function fitted using a widespread polynomial interpolator. This concept, further validated using MSE, established the fuzzy scheme's efficacy making it suit marine applications (Punarselvam et al. 2020; Vijaya Kumar et al. 2020). Elaboration of the concerned modules is detailed in the following sections.

3.1 Adaptive longitudinal path strategy

FMCAS provides longitudinal acceleration in proportion to the front, rear vehicle distance, and velocity. An instant motion control for this scenario is estimated using different fuzzy sets and fuzzy variables (Priyadarshni and Sudhakar 2015). The input variable, Front Vehicle Distance (FVD), is fuzzified into fuzzy sets, namely no curve (NC), short (S), lightly medium (LM), medium (M), more medium (MM), and long (L). Also, Rear Vehicle Distance (RVD) is fuzzified as very short (VS), shorter (MS), short (S), lightly short (LS), lightly medium (LM), medium (M), more medium (MM), and long (L). Likewise, the velocity parameters Rear Vehicle Velocity (RVV) and Host Vehicle Velocity (HVV) serving as input variables are fuzzified as very very slow (VVS), very slow (VS), short (S), lightly (LM), medium (M), more medium (MM), fast(F), very fast(VF) and superfast (SF). The fuzzy output variable, Estimated Host Vehicle Velocity (EHVV), concerned with the future vehicle dynamics are fuzzily mapped in accordance with the aforesaid fuzzy input variables. Moreover, Figs. 4, 5, and 6 illustrate membership functions of input and output parameters of all three vehicles, namely Front, Host, and Rear.

Based on vehicle dynamics, fuzzy rule Tables 2, 3, and 4 are designated by FMCAS to provide adaptive longitudinal motion under different vehicle conditions. Proportional acceleration or deceleration of the host (mid) based on the front and rear vehicle distance is fuzzified by FMCAS using these tables to attain constrained trajectories (Pushpalatha

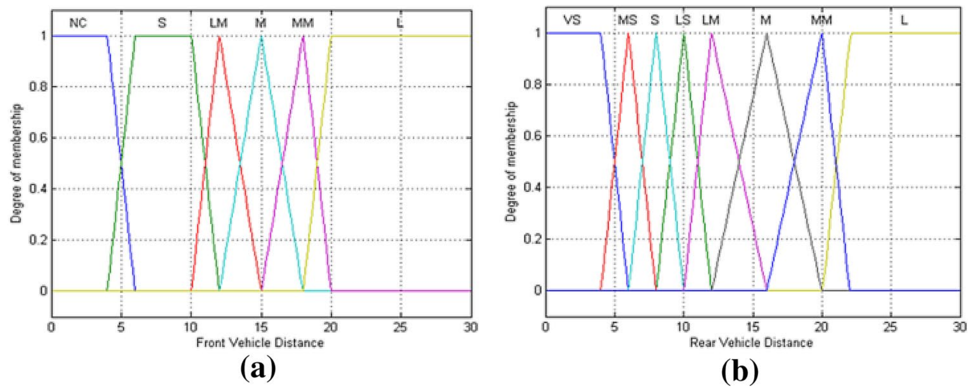

Fig. 4 Fuzzy sets of **a** Front Vehicle Distance (FVD). **b** Rear Vehicle Distance (RVD)

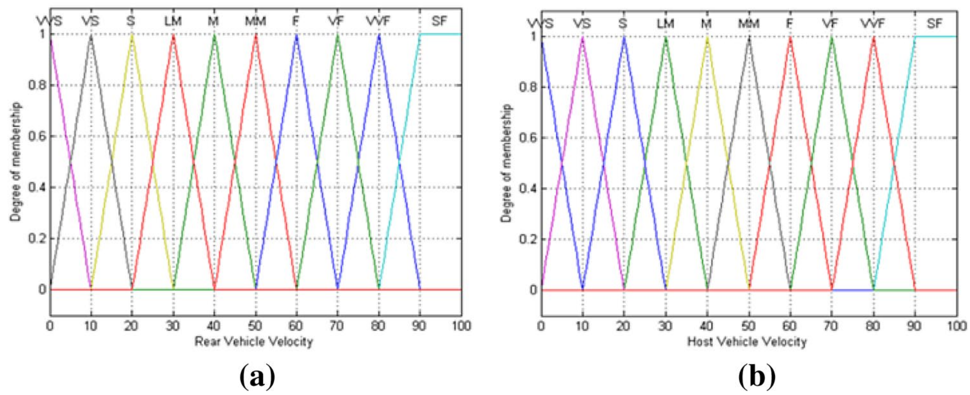

Fig. 5 Fuzzy sets of **a** Rear Vehicle Velocity (RVV). **b** Host Vehicle Velocity (HVV)

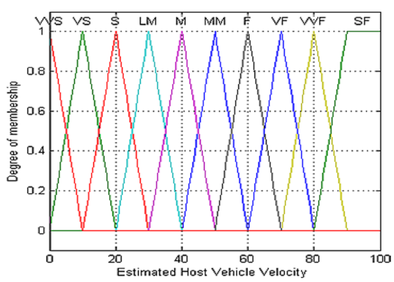

Fig. 6 Fuzzy sets of Estimated Host Vehicle Velocity (EHVV)

et al. 2020; Qingquan et al. 2014; Rodriguez-Castano et al. 2016).

Fuzzy Table 2 addresses explicitly the condition where the rear vehicle is at the tail of the host and the non-existence of the front vehicle. Under such scenarios, FMCAS provides longitudinal motion to the host by fuzzy tuning the EHVV in proportion to RVV. Fuzzy rules presented in Table 2 are framed based on the parameters FVD, RVD, RVV, and HVV that are uniquely tuned to produce EHVV.

Another set of fuzzy rules is presented in Tables 3 and 4 for addressing specific scenarios wherein the front, mid

Table 2 Relative distance between host and rear vehicle to avoid rear-end collision

EHVV*			HVV								
FVD	RVD	RVV	VVS	VS	S	LM	M	MM	F	VF	SF
TL	VS, MS, S, LS, LM, M, MM, L	VVS	VVS	VS	S	LM	M	MM	F	VF	SF
		VS	VS	VS	S	LM	M	MM	F	VF	SF
		S	S	S	S	LM	M	MM	F	VF	SF
		LM	LM	LM	LM	LM	M	MM	F	VF	SF
		M	M	M	M	M	M	MM	F	VF	SF
		MM	MM	MM	MM	MM	MM	MM	F	VF	SF
		F	F	F	F	F	F	F	F	VF	SF
		VF	VF	VF	VF	VF	VF	VF	VF	VF	SF
		SF	SF	SF	SF	SF	SF	SF	SF	SF	SF

Table 3 Stepping down the host vehicle velocity

EHVV*			HVV								
FVD	RVD	RVV	VVS	VS	S	LM	M	MM	F	VF	SF
LM	M	VVS	VVS	VVS	VS	S	LM	M	MM	F	VF
M	MM	VS	VVS	VVS	VS	S	LM	M	MM	F	VF
MM	L	S	VS	VS	VS	S	LM	M	MM	F	VF
		LM	S	S	S	S	LM	M	MM	F	VF
		M	LM	LM	LM	LM	LM	M	MM	F	VF
		MM	M	M	M	M	M	M	MM	F	VF
		F	MM	MM	MM	MM	MM	MM	MM	F	VF
		VF	F	F	F	F	F	F	F	F	VF
		SF	VF	VF	VF	VF	VF	VF	VF	VF	VF

Table 4 Stepping up the host vehicle velocity

EHVV*			HVV								
FVD	RVD	RVV	VVS	VS	S	LM	M	MM	F	VF	SF
M	LM	VVS	VS	VS	S	LM	M	MM	F	VF	SF
MM	M	VS	S	S	S	LM	M	MM	F	VF	SF
L	MM	S	LM	LM	LM	LM	M	MM	F	VF	SF
		LM	M	M	M	M	M	MM	F	VF	SF
		M	MM	MM	MM	MM	MM	MM	F	VF	SF
		MM	F	F	F	F	F	F	F	VF	SF
		F	VF	VF	VF	VF	VF	VF	VF	VF	SF
		VF	SF	SF	SF	SF	SF	SF	SF	SF	SF
		SF	SF	SF	SF	SF	SF	SF	SF	SF	SF

(host), and rear vehicles are running at different velocities and the distance between them varies dynamically.

In such situations, the FMCAS imposes a tight constraint on the host to relatively maintain appropriate distance and velocity. Fuzzy rule Table 3 describes the linguistics for marginally decreasing the HVV of the host to produce EHVV. EHVV aids in the further manoeuvring of the host vehicle by relatively maintaining the distance between the front and rear vehicles (Sasi Kala Rani et al. 2020; Satheesh et al. 2020a, b).

Similarly, fuzzy rule Table 4 lists the rules for the marginal variation of HVV of the host that different tunes EHVV to maintain the appropriate distance between the vehicles. For the longitudinal path estimation, the fuzzy rule table is modeled and enlisted in this research article addressing the different road scenarios between the front, host, and rear vehicles based on the distance parameter.

Although the relative distance is maintained by the host using the fuzzy rules composed in Tables 2, 3, and 4, the aforementioned strict constraint is not possible under rigorous road conditions. To address such situations, an offset-based curvilinear model is adapted by the FMCAS.

3.2 A suitable (OFFSET) curvilinear path estimation

Front and rear vehicles are traveling at low and high speed, respectively, the risk of collisions with the host is higher. Under such constraints, an intelligent curvilinear motion is preferred where longitudinal acceleration or deceleration is not possible to avoid the imminent collision. Intelligent navigation involves fitting path schemes that interpolate the path between starting and destination point without hitting the front vehicle edges, as illustrated in Fig. 7.

Parameters off_H *and* off_F witnessed in Fig. 7b reveals offset (*off*) position to be incorporated for vehicle steering as given below.

$$off = off_F - off_H \tag{8}$$

The offset value determines the adjustment requirement across *y*-coordinate depending on the front vehicle position, as illustrated in Fig. 7b. Initially, the path coordinates are formulated by FMCAS based on the offset position of the front vehicle using Eqs. (9), (10), and (11) that account

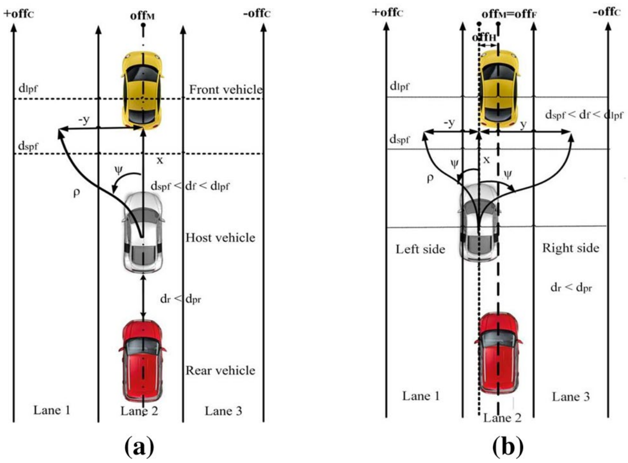

Fig. 7 **a** Fixed curvilinear motion. **b** Adaptive motions based on real-time scenario

for the x_t, $y_{t,left}$ and $y_{t,right}$ coordinates respectively for steering right and left side directions of the host vehicle.

$$x_t = Kt \tag{9}$$

$$y_{t,right} = \frac{y_{max} + off}{1 + be^{ax_t}} - y_{right}(0) \tag{10}$$

$$y_{t,left} = -\frac{y_{max} - off}{1 + be^{ax_t}} + y_{left}(0) \tag{11}$$

The K parameter from Eq. (9) is sampling time along 'x' coordinates. Also, the Parameters $y_{right}(0)$, $y_{left}(0)$are the initial value from (10) and (11), which nullifies the 'y' coordinates at zeroth time. The constant terms (a,b) from the Eqs. (10) and (11) assist in the convenient trajectory fitting of the host vehicle.

The trajectories of collision avoidance are modeled with ESRs (sensor system) vehicle kinematic data using MATLAB software shown in Fig. 8.

Upon evaluation of the respective position coordinates, FMCAS fits an adaptive curvilinear motion using the fuzzified

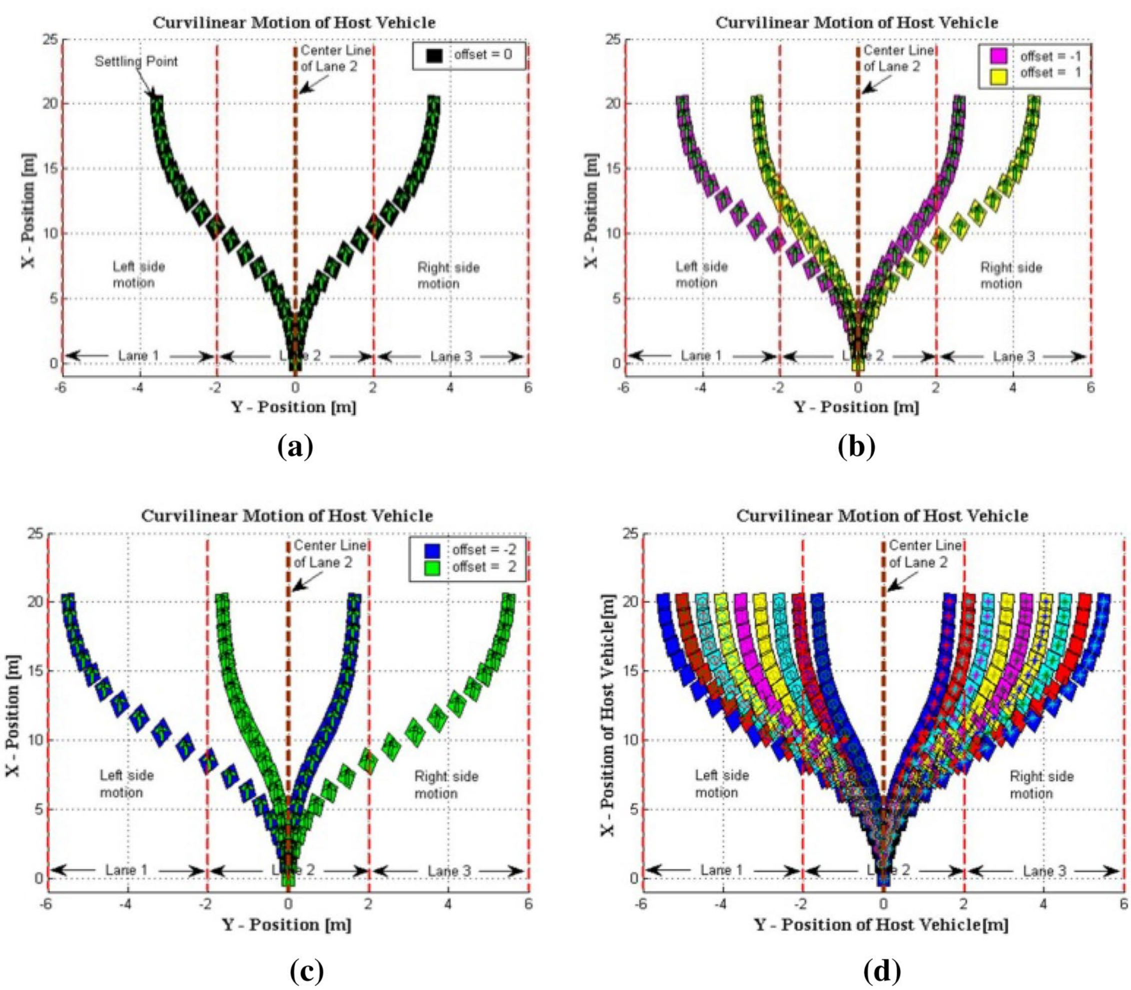

Fig. 8 Estimated trajectories of host vehicle for offsets (– 2, – 1.5, – 1, – 0.5, 0, 0.5, 1, 1.5, 2)

form of the Lagrangian interpolation technique. This hybrid novelty introduced in this paper is best suited for nonlinear and linear curve fitting applications. The Lagrange interpolation model presented in Eqs. (12–14) is fuzzified to evaluate the relevant position (x, y) coordinates at different time instants. This arrangement increases the number of consequences that enable FMCAS to address extreme road conditions. The variable' denotes the degree of membership function at 'y' position.

$$l_n(y_i) = \sum_{i=0}^{n} m_i L_{n,i}(y) \tag{12}$$

$$L_{n,i}(y) = \prod_{k \neq i}^{n} \frac{y - y_k}{y_i - y_k} \tag{13}$$

$$m_i = l_n(y_i) \forall \mathrm{i} = 0,1,2 \ldots \mathrm{n} \tag{14}$$

Consequently, FMCAS imposes fuzzy membership functions for fuzzy variables to model position estimation of the mid vehicle. The evaluated fuzzy *x, y* variables at each time instant are merged to fit an appropriate path using Eqs. (15) and (16). Moreover, the offsets (−2, −1, 0, 1, 2) concerned with the front vehicle position involve diverse coefficients ($A_{0,-2}..A_{4,-2}$, $A_{0,-1}..A_{4,-1}$, $A_{0,0}..A_{4,0}$, $A_{0,1}..A_{4,1}$, $A_{0,2}..A_{4,2}$) to produce different paths for both the left and right directions modeled in Eqs. (10) and (11).

$$m_{x_t,offset} = Ax_t \tag{15}$$

$$\begin{bmatrix} m_{y_t,-2} \\ m_{y_t,-1} \\ m_{y_t,0} \\ m_{y_t,1} \\ m_{y_t,2} \end{bmatrix} = \begin{bmatrix} A_{0,-2} & A_{1,-2} & A_{2,-2} & A_{3,-2} & A_{4,-2} \\ A_{0,-1} & A_{1,-1} & A_{2,-1} & A_{3,-1} & A_{4,-1} \\ A_{0,0} & A_{1,0} & A_{2,0} & A_{3,0} & A_{4,0} \\ A_{0,1} & A_{1,1} & A_{2,1} & A_{3,1} & A_{4,1} \\ A_{0,2} & A_{1,2} & A_{2,2} & A_{3,2} & A_{4,2} \end{bmatrix} \begin{bmatrix} y_t^5 \\ y_t^4 \\ y_t^3 \\ y_t^2 \\ y_t \end{bmatrix} \tag{16}$$

Based on (12), the fifth degree Lagrangian polynomial is fitted by FMCAS for rendering curvilinear motion mainly under different offsets. The values of coefficients presented in (16) pertaining to the steering directions right and left are evaluated using (12) and presented in Table 5.

Using the above analysis, FMCAS then constructs a novel membership function that is fitted with the crisp Lagrangian polynomials evaluated for offsets ranging between −2 to + 2, presented in (16). For offset-based steering, the host and front vehicle offset differences attained through (8) are further fuzzified by FMCAS into fuzzy sets, namely, negative two (NT), a negative one (NO), zero (Z), positive one (PO), positive two (PO). Also, the direction and time (*t*) are fuzzified as left, right, andt_0,t_1,... $t_{4.75}$ respectively. Similarly, the fuzzy outputs corresponding to x, y-positions are fuzzy formulated asx_0,x_1,... x_{19} andy_0,y_1,... y_{19} Respectively. Accordingly, the membership functions pertaining to fuzzy input and output variables are illustrated in Fig. 9, 10, 11, 12, 13, 14, and 15 that elaborate on the significant path estimation of the midvehicle based on the offset position of the front vehicle.

Fuzzification of *x* and *y* coordinates at different time instants and the consequences pertaining to *x*-position, *y*-position (left), *y*-position (right) are given in Tables 6 and 7. Since the *x* coordinate varies linearly with time, the interpolation remains the same for all the offset values, as witnessed in Table 6.

The fuzzy rule of Table 6 generalizes the *x*-coordinates for different offsets and time instants based on the fuzzified FVD, RVD parameters along with the direction. On the contrary, *y*-coordinate exhibits non-linearity with respect to time that tends to produce different constraint paths on both left and right directions of midvehicle. Hence, Fuzzy rules for separately addressing the midvehicle maneuver along the left and right directions are presented in Table 7, respectively. From the above discussions, it is evident that the FMCAS is also capable of addressing blind curvilinear motion (offset = 0) of front vehicles. FMCAS's offset-based curvilinear model is able to cater to the significant demand for an intelligent navigation system and also resolves similar

Table 5 A suitable coefficient values for various offsets

Directions	Coefficients	Offset				
		−2	−1	0	1	2
Left	A_0	−0.0029	−0.0075	−0.025	−0.12	−1.2
	A_1	−0.039	−0.084	−0.22	−0.78	−4.9
	A_2	−0.2	−0.36	−0.73	−1.9	−7.5
	A_3	−0.48	−0.7	−1.1	−2.1	−5.3
	A_4	−0.62	−0.75	−0.95	−1.3	−2.1
Right	A_0	1.2	0.12	0.025	0.0075	0.0029
	A_1	−4.9	−0.78	−0.22	−0.084	−0.039
	A_2	7.5	1.9	0.73	0.36	0.2
	A_3	−5.3	−2.1	−1.1	−0.7	−0.48
	A_4	2.1	1.3	0.95	0.75	0.62

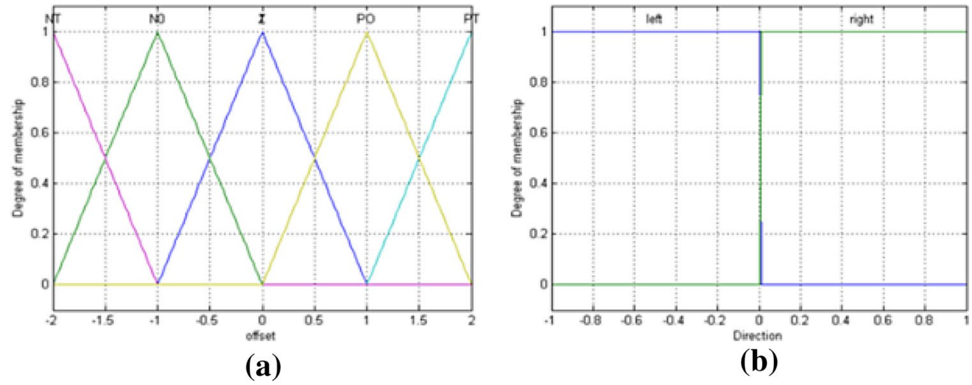

Fig. 9 Fuzzy sets of **a** offset. **b** Direction

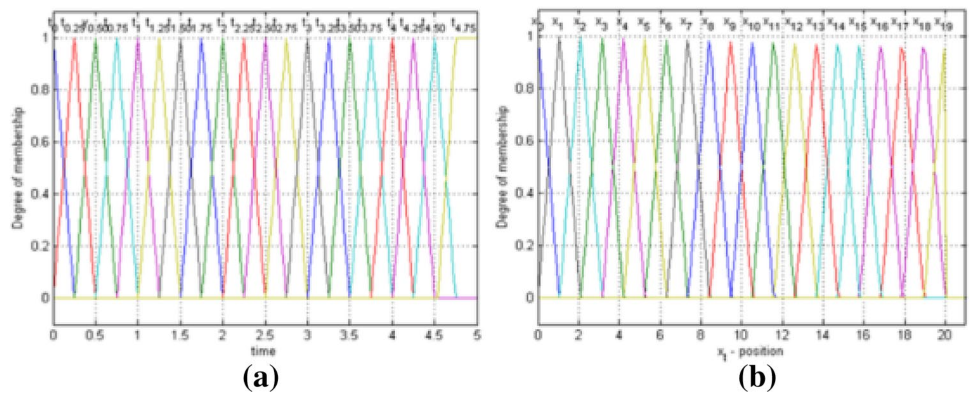

Fig. 10 Fuzzy sets of **a** time. **b** *x*-position

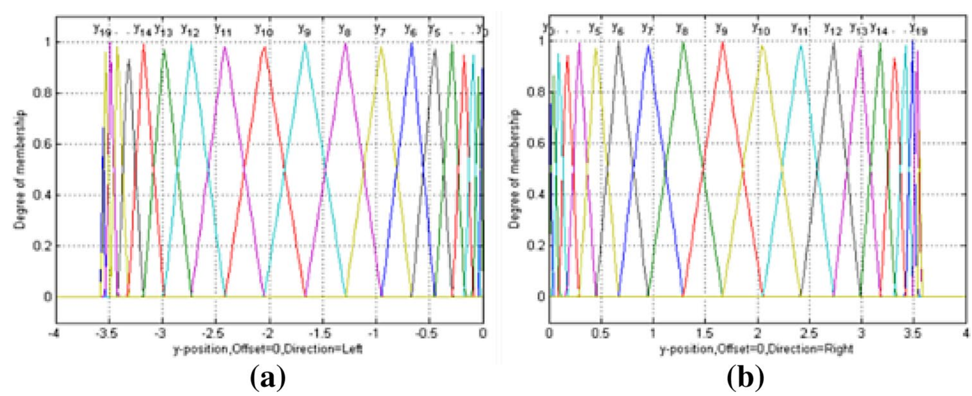

Fig. 11 Fuzzy sets of **a** *y*-position for offset = 0 and direction = left. **b** *y*-position for offset = 0 and direction = right

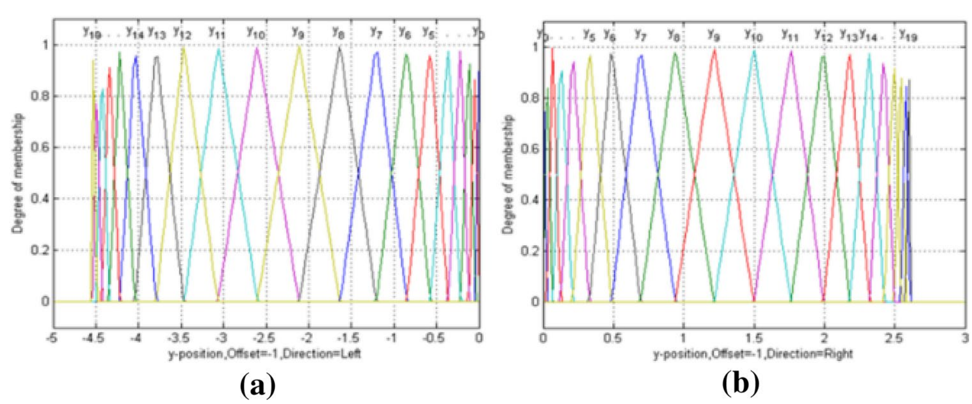

Fig. 12 Fuzzy sets of **a** *y*-position for offset = − 1 and direction = left. **b** *y*-position for offset = − 1 and direction = right

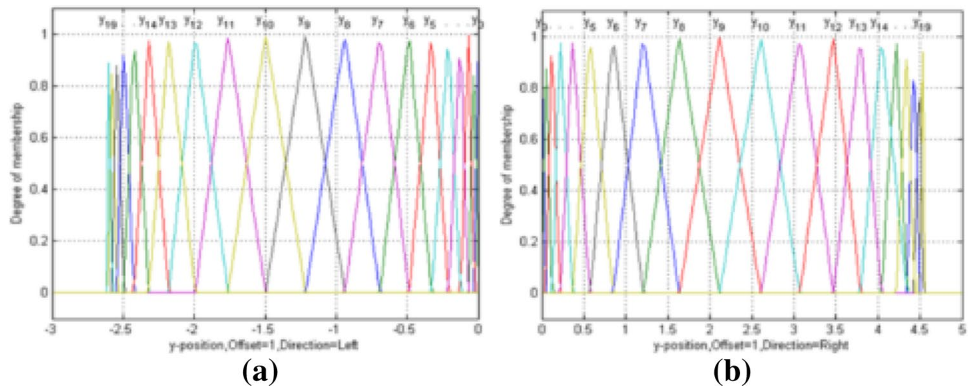

Fig. 13 Fuzzy sets of **a** *y*-position for offset = 1 and direction = left. **b** *y*-position for offset = 1 and direction = right

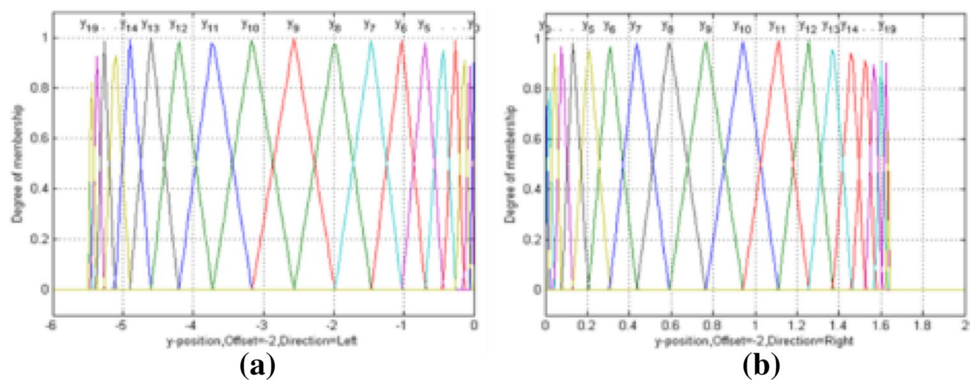

Fig. 14 Fuzzy sets of **a** *y*-position for offset = − 2 and direction = left. **b** *y*-position for offset = − 2 and direction = right

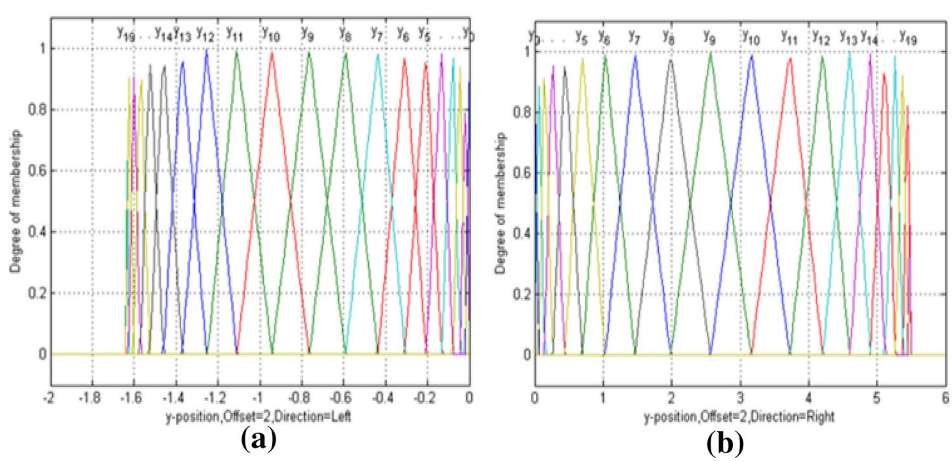

Fig. 15 Fuzzy sets of **a** *y*-position for offset = 2 and direction = left. **b** *y*-position for offset = 2 and direction = right

Table 6 x-position for curvilinear path estimation

Direction	FVD	RVD	Offset	*t* (time)						
				0	0.25	0.50	0.75	1	……	4.75
Left/Right	L	VS,MS, S, LS, LM, M, MM,L	− 2 − 1 0 1 2	*x(1)*	*x(2)*	*x(3)*	*x(4)*	*x(5)*	……	*x(20)*

Table 7 Curvilinear y-position for left and right direction of the host vehicle

Direction	FVD	RVD	offset	t(time)						
				0	0.25	0.50	0.75	1	……	4.75
Left/right	L	M	−2	y(0)	y(1)	y(2)	y(3)	y(4)	……	y(20)
			−1	y(0)	y(1)	y(2)	y(3)	y(4)	……	y(20)
			0	y(0)	y(1)	y(2)	y(3)	y(4)	……	y(20)
			1	y(0)	y(1)	y(2)	y(3)	y(4)	……	y(20)
			2	y(0)	y(1)	y(2)	y(3)	y(4)	……	y(20)

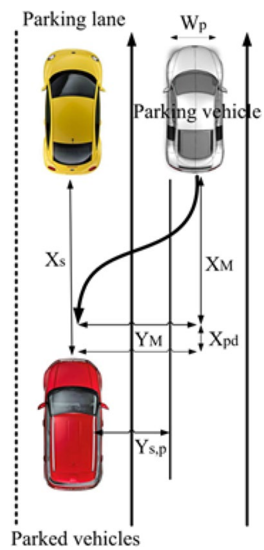

Fig. 16 Reverse trajectory for parallel parking model

parking issues. Fuzzy linear regression is a mathematical design to address a longitudinal path strategy addressing more collision scenarios in real-time conditions. Additionally, the lateral motion is fuzzified based on the respective coordinates (y coordinate with respect to x). In the lateral path estimation, the number of triangular memberships is framed with respect to the maximum lateral coordinate.

3.3 Parallel Parking model

The introduced FMCAS concept is further extended to parallel parking scenario owing to the inherent curvilinear path fitting mechanism. Generally, parallel parking involves path fitting strategy in the reverse direction by the parking vehicle to settle down at the specified point, as shown in Fig. 16. The distance measuring sensors estimate the maximum distance along 'x' (longitudinal) and 'y' (lateral) directions through which a definite curvilinear path could be designed for this application.

The sensor system measures the amount of maximum x-distance (x_m) and y-distance (y_m) based on maximum distance (x_s) between parked vehicles, predefined distance (x_{pd}), parked vehicle distance ($y_{s,p}$), and half of the width of parking vehicle ($\frac{W_P}{2}$) as given in equations.

$$x_m = x_s - x_{pd} \tag{17}$$

$$y_m = y_{s,p} + \frac{W_p}{2} \tag{18}$$

A constant K term in Eq. (19) and coefficients a, b in Eq. (20) play a vital role in x-position and y-position to fit the suitable path for the parallel parking application. The minus sign indicated in Eqs. (19) and (20) shows the reverse and left the direction of the parking vehicle.

$$x_t = -Kt \tag{19}$$

$$y_t = \frac{-y_{max}}{1 + be^{ax_t}} + \mathrm{y}(0) \tag{20}$$

Similar to offset based curvilinear motion, parallel parking also adapts the Lagrangian interpolation model as defined in Eqs. (12–14) . As denoted in Fig. 16, offsets of hosts play a vital role in vehicle parking. Also, x-coordinate variation representing the distance between the parked vehicles is also accounted for by FMCAS. Hence, the fuzzified x, y coordinates are further interpolated at every in stantto fit an appropriate curvilinear path using Eq. (21), (22).

$$m_{x_t} = Ax_t \tag{21}$$

$$m_{y_t} = \begin{bmatrix} A_0 & A_1 & A_2 & A_3 & A_4 \end{bmatrix} \begin{bmatrix} y_t^5 \\ y_t^4 \\ y_t^3 \\ y_t^2 \\ y_t \end{bmatrix} \tag{22}$$

To establish such a constraint, FMCAS employs fuzzy membership functions for the fuzzy variables to estimate the position of parking vehicles. The time, t being fuzzy input variable is fuzzified ast_0,t_1,...$t_{4.75}$. Similarly, x-position (fuzzy output variable) asx_0,x_1,... x_{19} and x-position (fuzzy output variable) asy_0,y_1,... y_{19} And are shown in Fig. 17. Further, the interpolation coefficients are inherited from the offset-based curvilinear model for this parking scenario. The fuzzy rule for the parallel parking scenario is stated in Table 8.

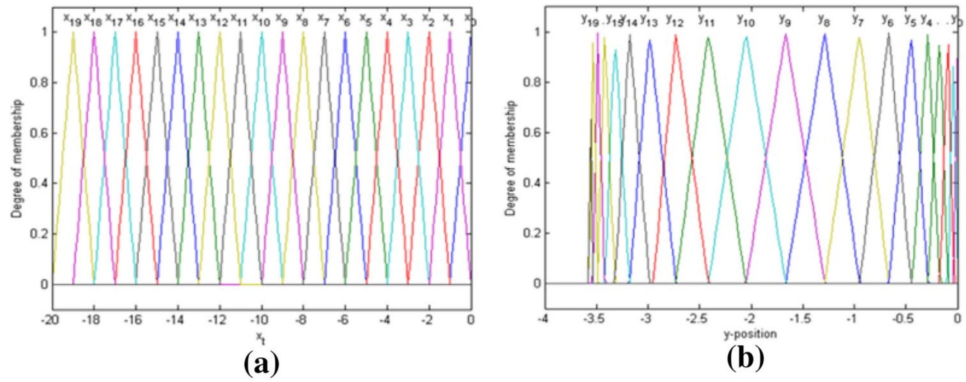

Fig. 17 Fuzzy sets of **a** x-positions in left direction. **b** Y-positions in reverse direction

Table 8 Interpolation for parallel parking

Time(t)	0	0.25	0.50	0.75	1	……	4.75
x-position	**− x(1)**	**− x(2)**	**− x(3)**	**− x(4)**	**− x(5)**	……	**− x(20)**
y-position	**− y(1)**	**− y(2)**	**− y(3)**	**− y(4)**	**− y(5)**	……	**− y(20)**

Fuzzy rule Table 8 describes the x and y-positions for parking vehicles in the reverse direction at different time instants. The minus sign tagged with x, y-coordinate indicates path estimation in reverse and left direction for parking vehicle. Thus, the fuzzified offset-based curvilinear model of FMCAS is capable of handling parallel parking applications.

To validate the extent of matching the crisp model and the intended fuzzy membership function, a detailed analysis using MSE is performed and presented in the following sections.

4 MSE analysis

Generally, MSE reveals the amount of position error between estimated and actual position value for various time intervals given in (23). The actual position coordinates pertaining to p(x,y) evaluated using (9), (10), and (11) are compared against the fuzzy attained values using (15), (16) to perform the error analysis.

$$MSE = \frac{1}{n} \sum_{j=1}^{n} (\hat{p} - p)^2 \tag{23}$$

where p denotes actual position at (x, y) and $\hat{p}$ represents the estimated position. Accordingly, Table 9 discloses the average position error along with x and y coordinates, evaluated for different offsets (−2, −1, 0, 1, 2).

The average traction error is evaluated using a 20-point 5th-degree polynomial. From Table 9, an MSE of 3.9443×10^{-28} m observed for the x-coordinate under different offsets reveals the closeness of the designed membership function with the Lagrangian polynomial. An attribute is mainly owed to the fitting coefficient (A). Likewise,

Table 9 MSE for x and y-coordinates for various offsets

Directions	Offset	x-position	y-position
Left	−2	3.9443×10^{-28}	0.2587
	−1		0.7210
	0		0.3069
	1		0.0587
	2		0.0148
Right	−2		0.0148
	−1		0.0587
	0		0.3069
	1		0.7210
	2		0.2587

y-coordinate MSE is maximally bounded at 0.7210 m for the offset + 1 m and minimal at 0.0148 m for an offset of −2 m. From the aforesaid discussions, it is evidentially established that the novel membership function closely resembles the actual crisp model and is able to deliver better performance.

5 Conclusion

The proposed graphical interfacing describes a collision avoidance scheme using fuzzy. The fuzzification concept mainly increases the number of consequents that can be addressed by the crash detection and avoidance system, which is absent in the prevailing crisp models. The proposed FMCAS avoids the imminent collision by delivering various motion models. Also, FMCAS determines to proceed with either longitude or offset-based curvilinear motion based on critical environments. In specific cases, the host vehicle engaged between the front and the rear vehicles, a suitable curvilinear, is rendered by FMCAS without threatening the front vehicle. Furthermore, FMCAS overcomes the blind curvilinear motion problem, which remains a significant bottleneck for any intelligent navigation system in the automotive domain. The introduced novel fuzzy membership function caters to the offset-based curvilinear motion and, more specifically, the parallel parking scenario in the reverse direction. MSE values of 3.9443×10^{-28} m for x-coordinate and the y- coordinate ranging between 0.0148 m to 0.7210 m for different offsets (− 2, 1, 0, 1, 2) observed for the actual and the estimated path signifies the potential of FMCAS. Kinematic analysis of FMCAS discloses intelligent motion for diverse road conditions that can handle complex situations and further paves the way for adaptive modeling.

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