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Adaptive Behaviour Selection for Autonomous Vehicle Through Naturalistic Speed Planning

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Abstract— **As autonomous technologies in ground vehicle application begin to mature, there is a greater acceptance that they can eventually exhaust human involvement in the driving activity. There is however still a long way to go before such maturity is seen in autonomous ground vehicles. One of the critical limitations of the existing technology is the inability to navigate complex dynamic traffic scenarios such as non-signalised roundabouts safely, efficiently and while maintaining passenger drive comfort. The navigation at roundabouts has often been considered as either a problem of collision avoidance alone or the problem of efficient driving (reducing congestion). We argue that for any autonomous planning solution to be accepted for replacing the human driver, it has to consider all the three objectives of safety, efficiency and comfort. With human drivers driving these complex and dynamic scenarios for a long time, learning from the human driving has become a promising area of research. In this work, we learn human driver's longitudinal behaviours for driving at a non-signalised roundabout. This knowledge is then used to generate longitudinal behaviour candidate profiles that give the autonomous vehicle different behaviour choices in a dynamic environment. A decision-making algorithm is then employed to tactically select the optimal behaviour candidate based on the existing scenario dynamics. There are two important contributions in this paper, firstly the adaptive longitudinal behaviour candidate generation algorithm and secondly the tactical, risk aware, multi-objective decision-making algorithm. We describe their implementation and compare the autonomous vehicle performance against human driving.**

Keywords— Path Planning, Naturalistic Speed Planning, Behaviour Planning, Trajectories, Situation Awareness, Risk Aware.

I. INTRODUCTION

For a long period of time before all the vehicles on the road are autonomous and can communicate their intentions, they will co-exist with semi-autonomous and human-driven vehicles. In such a situation it is necessary for the autonomous vehicle to be able to understand its surrounding scenario context, predict its evolution and generate plans that will enable its successful navigation. To give the vehicle this capability of generating adaptive behaviours a novel behaviour planning concept was suggested in our previous work [1]. The autonomous control software architecture that encompasses the behaviour planning module was also developed and tested in simulation and real-world environment [2]. In this work, we describe the adaptive behaviour selection algorithm which complements the behaviour planning methodology for an autonomous vehicle described in [1]. With the case of a non-signalised roundabout, we demonstrate how an autonomous vehicle can adaptively generate multiple candidate behaviour plans based on the current scenario and use a risk-aware multi-objective decision-making algorithm to select the optimal behaviour to execute a successful navigation. The decision making to select the optimal behaviour manoeuvres at non-signalised roundabouts is an existing problem for autonomous vehicles. Here, the types of manoeuvres chosen are dependent on multiple factors such as traffic rules, priority interpretation, the motion intentions of other actors etc. In such an interaction dependent scenario, the behaviour of other actors in the scene can be dynamically changing and sometimes non-predictable. This makes the requirement of generating multiple behaviours candidates for the autonomous vehicle decision-making non-trivial.

Experienced human drivers have shown the ability to master the art of navigating complex scenarios such as non-signalised roundabouts with a combination of manoeuvre planning and tactical decision making. Considering the scenario of a single lane non-signalised 4- exit roundabout, we learn the art of how human drivers control the vehicle motion in the presence and absence of conflict in its motion path. The learnings are then used in generating naturalistic longitudinal behaviour candidate profiles. We also provide the provision to make the candidate profile generation adaptive, encompassing the dynamic scenario factors such as speed limits and current vehicle speed. We then embed this with the risk-aware decision-making algorithm to form a behaviour selection module for an autonomous vehicle. The developed solution is then compared to the human driver for efficiency, safety and driving comfort.

A. Related Work

Human driver's longitudinal behaviour has been studied in great detail for applications such as ADAS, traffic simulation studies and human factor studies. In ADAS applications the learnings have been used to develop strategies for functions such as

Adaptive Cruise Control (ACC)[3], [4] Emergency Braking (EB) [5], Anti-Lock Braking System (ABS) [5] etc. In Human Factor Studies, the learnings have enabled classifications to differentiate the driver's skill level and also insight into how different type of driving behaviours lead to accidents etc.[6]–[8]. More recently attempts have been made to understand the human driving behaviours and strategies to aid autonomous driving decision making in complex traffic scenarios. As experienced human drivers have shown the ability to adapt their longitudinal speed behaviours and strategies to effectively navigate complex traffic scenarios, human-inspired longitudinal speed control is considered a promising direction for the autonomous vehicle application. This approach has two obvious advantages, the first one being that the autonomous vehicle driving will be more naturalistic [9], which will help it to seamlessly integrate into environments with other semi-autonomous and human driven vehicles and secondly it will improve the driving experience, especially in scenarios that are prone to stop-start motion or roads with high curvature [10]. One such study was seen carried out for an intersection scenario where clustering technique was used to match the human driving data from a simulator [11]. The cluster profiles were then used for autonomous driving using a collision avoidance decision-making algorithm. Although the approach for longitudinal behaviour planning is similar to ours, the method of generating the candidate's profiles is very specific to the recorded scenario, and the profiles also are not adapted with scenario dynamics. Also, the decision-making process with only collision avoidance as an objective gives little consideration to the drive comfort.

II. THE APPROACH

For a single lane roundabout, once the global path is established, the lateral steering behaviour for the autonomous vehicle will be known, therefore in this work, we consider the navigation planning for merging at a single lane roundabout, as a longitudinal speed planning problem. The two parts of the adaptive behaviour selection module are discussed below.

A. Longitudinal Behaviour Profiles Generation

The path planning module of the autonomous vehicle specifies a look-ahead trajectory for a defined horizon in front of the vehicle. The spatial part of the trajectory is defined by the position coordinates and the orientation, while the temporal part is defined by the target velocity along the trajectory. When navigating a scenario that involves possible conflicts with the motion of other actors, it is important the speed planning generate profiles that are not conflicting with other actor's motion and also lead to a smooth continuous motion of the vehicle. It has been shown in in human driving studies at intersection both through simulation [11] and real world [10], that experienced human driver control this temporal motion in a continuous manner, which allows the other actors to interact and plan their respective motion with greater certainty. This has led to attempts to generate human-like motion trajectories for autonomous driving application especially to navigate complex scenarios [12]–[14]. In this work, we use the

same analogy by developing a novel speed profiles generation algorithm using Bezier curve method. We first conducted an experiment of human drivers navigating the single lane roundabout in different merging condition and extracted longitudinal behaviour shape patterns for different motion intention. These learned patterns are then used with other characteristics such as the existing entry speed, the roundabout speed and the exit speed etc. which are usually dictated by the scenario dynamics to generate longitudinal behaviour profiles. As the behaviour intention of the other actors cannot be predicted with certainty and also there are cases where the other actor can have "change-of-intention", the algorithm generates multiple behaviour candidate profiles. This gives the decision-making algorithm the possibility to select the optimal profile according to the existing scenario dynamics. The process of generating the candidate profiles are shown in Section II of this paper.

B. Risk Aware Decision Making

In autonomous path planning at a non-signalised roundabout, the planner is required to take into account the motion of the other actors and make decisions of its motion according to the scenario context. Typically, in human driving at intersections, it has been shown that the individual's decision making about when, and how to choose the manoeuvre/ manoeuvres, is dependent on their current state, the perceptions of the gaps with other actors, their knowledge of own car's performance and their knowledge of the road layout. Many of these parameters are not fixed and some also change dynamically throughout the actor navigation along the length of the roundabout, resulting in a wide range of behaviour possibilities. In the non-signalised roundabouts, it is also crucial that the priorities of merging defined by the road regulations are respected. Human drivers show a wide disparity in their interpretation of the merging priority, which manifests into some drivers being highly assertive, while some very defensive. The autonomous vehicle decision making should account for these behaviour possibilities and dynamically select the behaviour profiles that are safe, and optimal in travel time, and maintains drive comfort. In this work we are concerned with autonomous navigation of a non-signalised roundabout, the priority is established based on the UK Highway driving code 184 to 190 [15]. Using the Highway Code the decision-making algorithm has to evaluate the priority while selecting any particular speed profile by evaluating two main situations.

1. Another vehicle within the roundabout – Here, the vehicle in the intersection has priority, and the autonomous vehicle can only merge behind that vehicle if sufficient gap exists.
2. No vehicle within the roundabout – Here, the priority to merge is applied by the right-hand rule, i.e. the vehicle on the right has priority and the priority goes anti-clockwise.

The first situation is a clear-cut case for decision making, while the second situation presents a unique decision-making challenge for the autonomous vehicle. The second situation presents the possibility to merge before the priority vehicle if its arrival at the

Yield line / or the conflict point is sufficiently earlier than the priority lane vehicle. Therefore in this study, we have only considered the second situation for analysis. As the longitudinal behaviour of the other actors can change during their motion, any behaviour maneuverer chosen by the autonomous vehicle will have an associated risk. The behaviour selection decision making algorithm establishes an objective risk index for each candidate profile based on the time gap method. The risk index is re-calculated iteratively every fixed sampling time and involves the calculation of the Time-to-Yield-line ($TTYl$) and the Time-to-Conflict point ($TTCp$) of the involved actors using its sensed current state and expected future motion speed.

$$TTYl_{act} = d_{path,act} * v_{act}$$
$$TTCp_{act} = TTYl_{act} + d_{rdabt,path} * v_{rdabt,max}$$

Where the $d_{path,act}$ is the distance of the actor along its path to the Yield line, and v_{act} is the estimated velocity of the actor, $d_{rdabt,path}$, is the distance along the path within the roundabout from the Yield line to the nearest conflict point. This parameter is fixed for a geometry of the roundabout. $v_{rdabt,max}$ is the maximum speed achievable in the roundabout. The predicted future speed of the other actor is calculated using constant deceleration if its current speed is greater than roundabout speed or through constant speed propagation if its current speed is equal to or below the speed achievable in the roundabout. The same parameters are then calulated for the autonomous vehicle i.e. $TTYl_{sub}$ and $TTCp_{sub}$ for each of the candidate profile.

The other two parameters used in the decision-making function are the drive comfort index and the waiting time index. In this work, the drive comfort indexes for the candidate profiles of the subject vehicle are established from vehicle lateral acceleration. The lateral acceleration is known to be proportional to the longitudinal speed in curves [16] i.e. higher the speed within the roundabout, higher is the lateral acceleration and therefore increased driver discomfort. Any speed below the comfortable lateral acceleration is given a zero index, while the higher lateral accelerations are penalised using the penalty factor. Here the longitudinal acceleration and deceleration are not considered as they are controlled through the candidate profile generation. The waiting time index is established as the amount of speed reduction required, as compared to the maximum possible speed profile in non–conflict situation, i.e. if the roundabout was free of any traffic there would be no waiting time, while the index increases with every reducing speed profile. If the vehicle has to come to a complete stop it has the highest index and the higher waiting times are penalised using the penalty factor. The overall behaviour selection function is then formulated as an objective function, $'Q'$, which is minimized to find the candidate with the lowest penalty.

$$\min_{candidates} Q_{cand} = a * CI_{cand} + b * WTI_{cand}$$

Where 'a' and 'b' are tuning parameters to weigh the objectives based on preference. $'CI'$, and 'WTI', are comfort index and the waiting time index respectively. With the indexes derived above and the objective function the decision-making algorithm is shown in Table I.

TABLE 1: THE PSEUDOCODE FOR BEHAVIOUR PLANNER.

When approaching an intersection
1. If the size of the roundabout is small, use '$TTYl'$ otherwise use '$TTCp'$. (The threshold for roundabout size can be derived empirically)
2. Estimate the candidate time gap as For all candidates $$TimeGap_{Yl} = TTYl_{cand,i} - TTYl_{act}$$ $$TimeGap_{Cp} = TTCp_{cand,i} - TTCp_{act}$$ Where i = 1,2,3…. ,n (n - number of candidates)
3. For all non-stopping candidates, if there exist candidates with time gap greater than the safe gap, select the behaviour candidate among them with the minimum penalty index as the chosen behaviour profile.
4. If none of the non-stopping candidates have time-gap greater than the safe gap, determine non-stopping candidates that can pass behind the conflicting vehicle and select the candidate one with the minimum penalty.
5. If none of the non-stopping candidates exists which can pass behind the conflict actor, select to stop candidate for stopping at the Yield line, before finding a safe gap to exit.
6. For all optimal candidate behaviours, the stop behaviour is also chosen as a secondary emergency behaviour.

The real-time behaviour selection algorithm is described through the flow diagram in Fig 1.
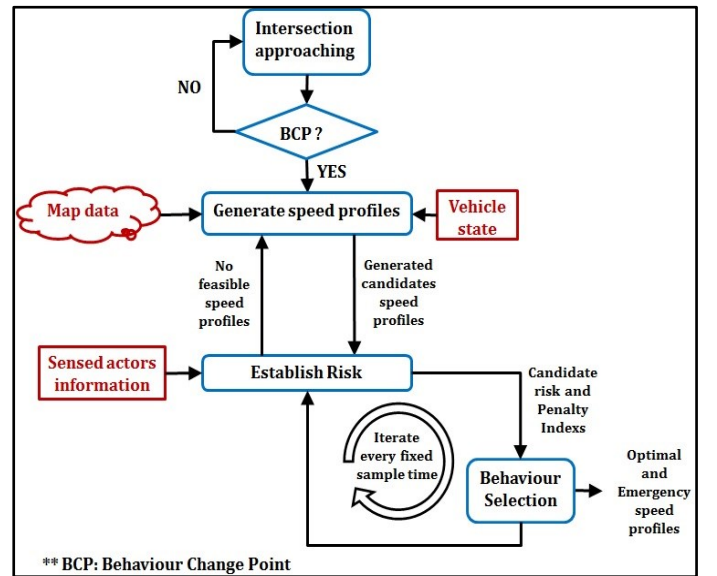

Fig. 1. Risk Aware Decision-Making Algorithm.

The rest of the paper is divided into 4 main sections. In Section III we describe the experimental study to record human longitudinal behaviour profiles. In Section IV we describe the analysis of the human driver data from the simulator study. In Section V we describe the results of the application of behavioural decision-making algorithm and compare the performance against human driver decision making. Finally, in section VI we conclude by summarising the work described in this paper and discuss the future work in this research direction.

III. THE EXPERIMENTAL STUDY

The objective of the experimental study was to gain insight into the human driver's longitudinal behaviour profiles and the decision-making at the non-signalised roundabout. The experimental set-up is explained through the driving scenario, the vehicle model and the vehicle control mechanism.

A. The Scenario.

The scenario consisted of a single lane 4 exit roundabout, with the subject vehicle and the actor vehicle approaching the intersection from two different entry points as shown in the bird's eye view in Fig 2. Two scenarios main cases were considered to capture driver's perception of risk and decision making when approaching the roundabout with another actor also approaching from the priority entry. The two cases are depicted in Fig 2.
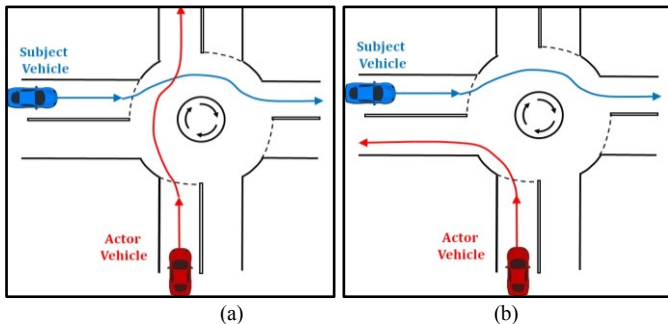

(a)   (b)
Fig 2. The simulator driving scenarios for (a) Case I and (b) Case II

CASE–I: Here the actor vehicle Follows-On to the second exit, thus there is an overlap of the intended path of the two actors
CASE-II: Here the actor vehicle takes the first exit, thus the path of the actor never overlap with the subject vehicle

To avoid the human driver pre-meditating the decision to stop or continue when approaching the intersection, they were not informed of the actor vehicle intention. This meant they had to make the decision in the dynamic scenario based on their perception and risk taking ability.

B. Vehicle Model

A vehicle plant model was required to provide the human driver with a realistic feedback of the control inputs. A dynamic vehicle model was used which provided the output motion based on the driver throttle and brake demand [11]. The suspension system stiffness, damping and maximum travel were calibrated to make the driving dynamics realistic. All the parameters of the vehicle were fixed including the vehicle mass so that there were no differences in the vehicle characteristics for the different participants.

C. Vehicle Control

1. The Lateral Control: Human drivers show variability in the lateral control of the vehicle which can lead to differences in the travelled distance, it also acts as a source of variation in the longitudinal behaviour. As in this study, the objective was to understand the variation in the longitudinal behaviour, the lateral control was automated, resulting in all drivers travelling exactly the same path. The human drivers were then only required control the vehicle longitudinal speed.

2. The Longitudinal Control: The driver accelerator pedal demand was converted through the vehicle powertrain model into traction force. The brake force was simulated as a percentage of the brake pedal percentage

$$F_{brake} = -k(BrkPdl)$$

Where the parameter k was empirically obtained. The net force after accounting for the drag resistance was then divided by the vehicle mass to obtain the acceleration and tham speed.

Before the actual recording, the human drivers were given trial runs to familiarise with the controls and only when they were sufficiently accustomed to the simulated driving task they were introduced to the different scenarios. 10 human participants were made to drive 14 scenarios with 7 different variations of the actor behaviour in each of the two cases. The 7 different variations in the actor's behaviour were obtained by changing the trigger point and its initial positions. The experiment resulted in 70 readings in each of the two cases, a total of 140 recordings of human driver longitudinal behaviour profiles.

IV. THE ANALYSIS

The human driver longitudinal behaviours were expected to vary depending on their anticipation of the conflict with the other actor and their risk taking in the merging manoeuvre. Analysing the longitudinal vehicle speed against the distance along the path of the subject vehicle, a wide spread of speed profiles were observed in both the scenario cases. While some drivers attempted to pass without stopping, others stopped even in the case of the actor vehicle was not in conflict. The speed profiles were classified into two categories for each case, which resulted in 4 categories, i.e

Follow-On No Conflict (FONC): Here the two vehicle paths did not overlap and the human driver continued the manoeuvre without coming to a stop at the Yield line.
Stop No Conflict (STNC): Here the two vehicle paths did not overlap, and the human driver still stopped at/close to the Yield line. This is a form of defensive driving.
Follow-On With Conflict (FOWC): Here the two vehicle paths did overlap, however, the human driver continued the manoeuvre without coming to a stop. This is a form of assertive driving.
Stop With Conflict (STWC): Here the two vehicle paths did overlap, and the human driver stopped at/close to the Yield line.

To visualise the spread of the data in each category, we used an Inter Quartile Range (IQR) box plot as shown Fig 3. Our intention of the analysis was to derive behaviour patterns for the different categories of longitudinal behaviours. As seen from Fig 3, the spread of the data is not symmetric along the length of the path, therefore we used median as a measure of the central tendency instead of the mean.
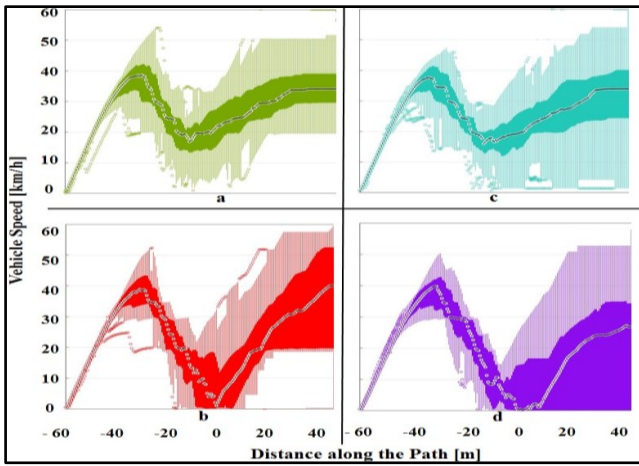
Fig 3. The IQR box plot for (a) FONC, (b) STNC, (c) FOWC and (d) STWC

Extracting the means of the 4 categories and plotting them another against the distance along the path is shown in Fig 4.
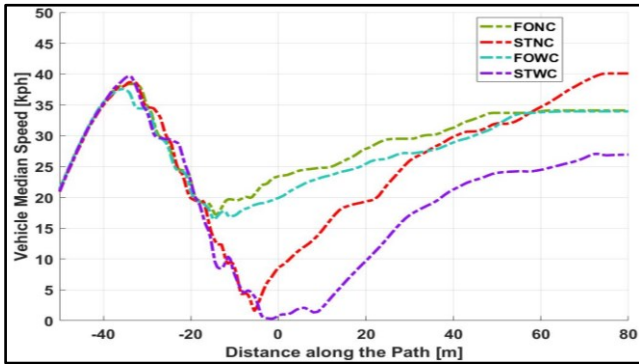

Fig 4. Median Behaviours for (a) FONC, (b) STNC, (c) FOWC and (d) STWC

The behaviour shape patterns obtained through our simulator study are similar to those obtained by M Coelho et al [17], for a single lane roundabout through empirical measurements. We describe the salient features of the behaviour patterns to incorporate them into the profile generation algorithm.

A. Salient Features

1. Curvature Limitations: The median profile suggests that in all categories the human drivers invariably slowed down from their existing speed to a median speed of 18-20 km/h. This behaviour can be primarily attributed to the curvature of the road limiting the speeds within the roundabout.
2. Defensive Driving: The median speed profile for STNC category suggests that many drivers came close to a complete stop and started to accelerate as soon as the no-conflict situation was comprehended.
3. Creeping Behaviour: The median speed profile for STWC suggests that many drivers first stopped and then tried to slowly creep forward before accelerating after the conflict situation no longer existed.
4. Manoeuvres Choice: The statistical analysis showed that the drivers made their choice to either follow on or stop at a

considerable distance before the Yield line. It was also seen from Fig 3 that the more than 50% of the Follow-On behaviours had intersection speeds from 12km/h-23km/h.
5. Crash Scenario: The zero/low-speed behaviour seen in FOWC and STWC was the consequence of a crash between the subject vehicle and the actor in conflict.

Having analysed the data of human driving, the longitudinal behaviour profile at roundabouts can be described as a series of three successive manoeuvres i.e. the approach to the roundabout the merging into the roundabout and the exit from the roundabout. In this work, we describe these three behaviour manoeuvres as phases and start from the point where the drivers showed an appreciable change in the longitudinal behaviour in the approach manoeuvre. We found that this behaviour point was approximately located around the human driver's anticipation of a safe stopping distance from the current speed. This point termed as a behaviour "changepoint" (BCP) is a function of the vehicle approach speed. The three phases of behaviour profile for a roundabout scenario is shown in Fig 5.
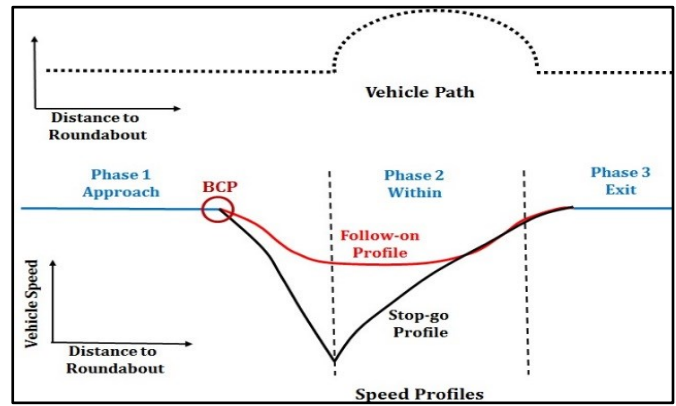

Fig 5. The Longitudinal Behaviour Phases for a Roundabout Scenario

B. The Candidate Generation

As seen in the experiments of human driving the approach to the roundabout is highly dependent on the manoeuvre chosen. If the driver chooses to continue without stopping at the Yield line, then they can continue to do the manoeuvres with the maximum possible speed. If however, the driver chooses to stop then the speed profile chosen should bring the vehicle to a stop at the Yield line before accelerating to the speed of the exit. These are the two possible extrema's for navigating the intersection. The experimental study also showed that a most of the driver's speed profiles were within the two extrema's, and the chosen speed profile is directly related to how the individual driver anticipation of the collision risk. Therefore, to generate naturalistic behaviour profiles using the Bezier curve approach matching the derived patterns to mimic human behaviours. The generation of the behaviour profiles to incorporate the regulatory factors such as speed limitation for entry and exit and also the curvature constraints through speed limit within the roundabout was

achieved using an adaptation mechanism of the Bezier control points. The algorithm first generates three pairs of Bezier curves, the first two pairs are for the Follow-On, and are generated using the control points shown in Fig 6, with the dynamic inputs of speed difference of entry and exits with the roundabout speeds $(\delta v_{en}, \delta v_{ex})$, the stopping distance (sd) the calibratble shape parameter (δ) and exit acceleration distance parameter (ed).
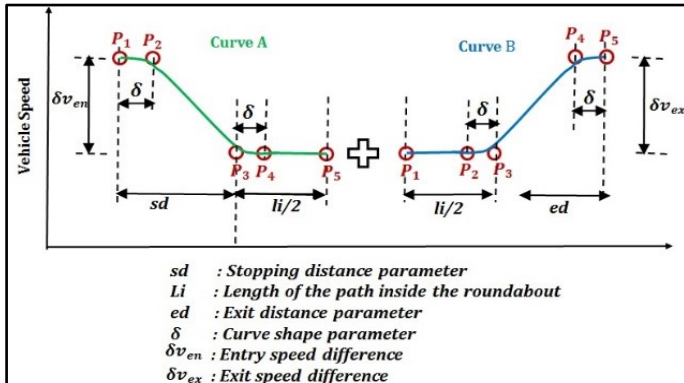

Fig 6. The Follow-On Behaviour Control Points

The stop behaviour profile pair of curves are also generated using the same analogy with control points shown in Fig 7
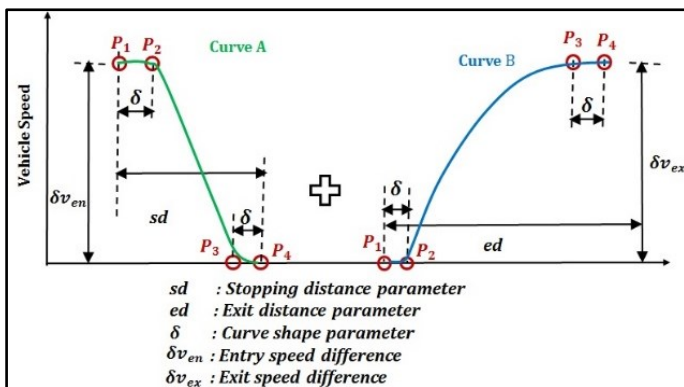

Fig 7. The Stop-On Behaviour Control Points

The pairs of curves are then concatenated to generate a continuous profile. By appropriate choice of the calibratable parameters, the shape of the profiles can be matched to any learned pattern generated from statistical data. To generate the rest of the candidate profiles for the follow-on behaviours, a fast interpolation technique was employed to reduce the computational burden of constructing all through the Bezier curve approach. The candidate behaviour profiles were generated through scenario specific adaptable speed control points and the terminology used for defining the profiles was also the value of control points speed i.e. if the entry speed is 40km/h, intersection speed is 20 km/h and exit speed is 40km/h, then the behaviour profile set will be named as 40-20-40. Fig 8 shows the 40-20-40 behaviour candidate profiles generated for a current scenario.
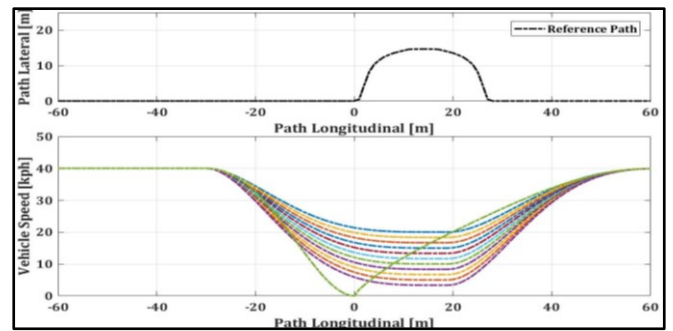

Fig 8. Behaviour Profiles for 40-20-40.

V. RESULTS AND DISCUSSION

To objectively compare the performance of the decision-making algorithm, we ran the autonomous vehicle in the same 14 scenarios of as the human drivers. To demonstrate different levels of risk-taking ability, the autonomous vehicle was calibrated to two different settings for safe time-gap, 0.7s for assertive driving 0.7s, and 1.5s for defensive driving. The performance was then measured using three performance indexes

1. The number of successful passes before the priority vehicle. This performance index classified drivers as either assertive or defensive. Successful assertive manoeuvres reduce waiting time and hence lead to efficient driving. Drivers with a successful pass before attempts of greater than 4 were termed as assertive drivers, while others were termed as defensive.
2. The number of collisions: This performance index indicated the skill level of the driver to avoid collision through predictive risk assessment. It highlights driver's ability to drive safely.
3. Speed differential at Entry: This performance index described the ability of the driver navigate the scenarios with minimum speed differential which leads to comfort driving. The speeds above the suggested max speed also lead to a negative performance on drive comfort.
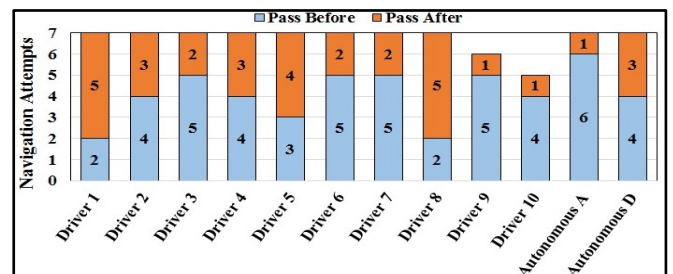

Fig 9. Number of Successful Navigation Passes

As seen in Fig 9 some human drivers were able to judge the scenario better than others and were able to make more successful passes before the priority lane vehicle. The autonomous vehicle with the assertive setting was able to perform better than human vehicle while the defensive also showed good performance. Human drivers generally show variability in decision making which results in them sometimes driving the same scenario differently. An autonomous vehicle, however, is more consistent in the speed selection and therefore has higher successful passes.
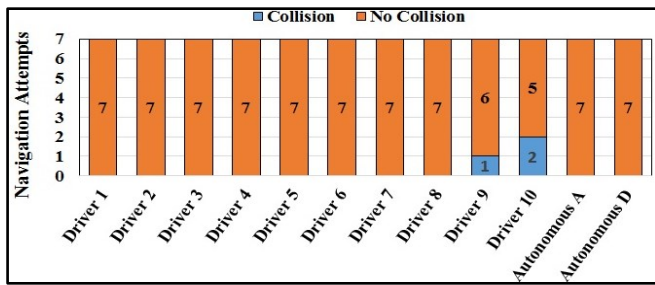
Fig 10. No of Collisions

Fig 10 shows the two human drivers ended up with collisions with the actor vehicle. As seen in Fig 9, these drivers were from the assertive group, however, could be termed as unskilled/ unsafe as they were not able to judge the scenario as well as the other assertive drivers or the autonomous vehicle.
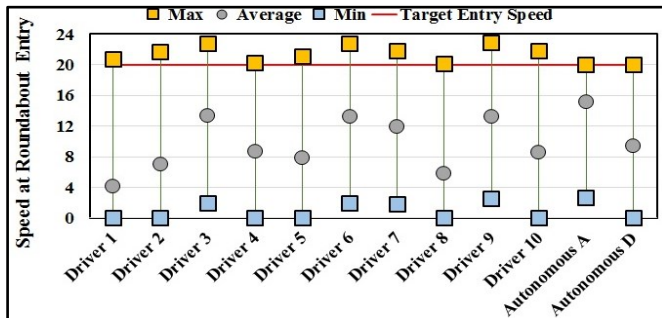

Fig 11. Speed Differential of Each Driver at Roundabout Entry

Many of the human drivers exceeded the target max speed at the entry of the roundabout and also had average speed far below the target speed suggesting that there were considerable decelerations. Both these behaviours contribute towards driver discomfort. This co2uld be attributed to the expected disregard for the vehicle lateral acceleration by human drivers when driving a simulator vehicle. The assertive autonomous vehicle performed better than all the human-driven vehicle.

VI. CONCLUSION AND FUTURE WORK

In this work, a concept of naturalistic longitudinal behaviour selection algorithm for autonomous ground vehicle application was demonstrated. This algorithm used risk-aware decision-making approach to select human-like longitudinal behaviour profiles for navigating a roundabout scenario. First, the speed profiles were generated using patterns learned from human driving and then they are adapted online with the dynamic scenario characteristics. There are two new contributions in this work, firstly the naturalistic profile generation for human-like navigation and secondly, the risk aware multi-objective decision-making approach, that accounts for drive comfort, drive efficiency in addition to drive safety. The performance of the proposed solution was compared with human driving data from experimental study, which showed encouraging advantages. The next phase of development of this work involves testing this algorithm in real, world mock-up environment. We also, intend to

see how this algorithm is suited for other types of road layouts such as multi-lane intersections etc.

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