Autonomous Navigation in Interaction-Based Environments—A Case of Non-Signalized Roundabouts

Maradona Rodrigues, Andrew McGordon, Graham Gest, and James Marco

***Abstract*—To reduce the number of collision fatalities at crossroads intersections, many countries have started replacing intersections with non-signalized roundabouts, forcing the drivers to be more situationally aware and to adapt their behaviors according to the scenario. A non-signalized roundabout adds to the autonomous vehicle planning challenge, as navigating such interaction-dependent scenarios safely, efficiently, and comfortably has been a challenge even for human drivers. Unlike traffic signal-controlled roundabouts, where the merging order is centrally controlled, driving a non-signalized roundabout requires the individual actor to make the decision to merge based on the movement of other interacting actors. Most traditional autonomous planning approaches use rule-based speed assignment for generating admissible motion trajectories, which work successfully in non-interaction-based driving scenarios. They, however, are less effective in interaction-based scenarios as they lack the necessary ability to adapt the vehicle's motion according to the evolving driving scenario. In this paper, we demonstrate an adaptive tactical behavior planner (ATBP) for an autonomous vehicle that is capable of planning human-like motion behaviors for navigating a non-signalized roundabout, combining naturalistic behavior planning and tactical decision-making algorithm. The human driving simulator experiment used to learn the behavior planning approach and the ATBP design is described in this paper.**

***Index Terms*—Adaptive tactical behaviour planner, adaptive control, human factors, naturalistic driving, trajectory planning.**

I. Introduction

CURRENTLY autonomous or self-driving vehicles are at the heart of academia and industry research because of their multi-faceted advantages that include improved safety, reduced congestion, lower emissions, greater mobility etc. Significant advancement in digital technology (sensing, processing etc.) has pushed the autonomous technology in ground vehicle applications from idealistic conceptual projects such as Navlab [1], VaMP [2], the PROMETHEUS Programme [3], ARGO Project [4] to the demonstration of realistic fully autonomous vehicle technology in the DARPA completion events [5], [6]. Since the DARPA challenges, the autonomous ground vehicle technology has been demonstrated in numerous public roads. Some of the most publicised of these include the VisLab Intercontinental Autonomous Challenge (VIAC) in 2010 [7], the Hyundai Autonomous Challenge in 2010 [8], the autonomous drive with Mercedes Bertha-Benz in 2013 [9], the Public Road Urban Driverless (PROUD) car testing in 2013 [10] and the Google self-driving car testing since 2009 [11]. The abovementioned trials have since been followed by many other players joining the efforts to move the autonomous vehicle technology closer to reality [12]. Nonetheless, the number of autonomous disengagements and incidences reported every month [13], [14], highlights that autonomous vehicle technology has still not fully matured. The analysis of these autonomous disengagement and collision reports show that most of them were in situations of high traffic activity which include intersections such as at T-junctions, crossroads, roundabouts etc., highlighting the limitations of the current state-of-art autonomous motion planning systems in successfully dealing with such real-world scenarios.

With potential benefits of reducing collisions, waiting time at intersections, improving fuel efficiency and reducing emissions of air pollutants, and improving traffic flow [15], [16], countries around the world have started to replace traffic signal controlled intersections with non-signalised roundabouts [17], [18]. The non-signalised roundabouts are high-interaction based driving environments, and the capability of the autonomous vehicle to navigate such scenarios depends greatly on their ability to generate adaptive motion behaviours in the continuously evolving driving environments. Successful autonomous navigation planning in such merging scenarios should also ensure that their motion behaviour does not create confusion among other road users, which will be the critical determinant of their co-existence with other semi-autonomous and manually driven vehicles. This paper describes a novel approach to autonomous behaviour planning called Adaptive Tactical Behaviour Planner (ATBP). The ATBP is part of the research work in developing human-like behaviour planning method for autonomously navigating highly dynamic interaction based scenarios safely, efficiently and with good driving comfort.

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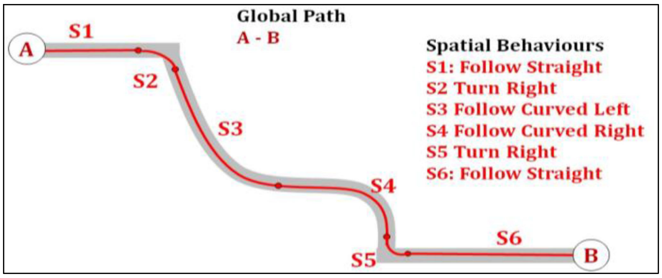


Fig. 1. Vehicle spatial behaviours on a global path.

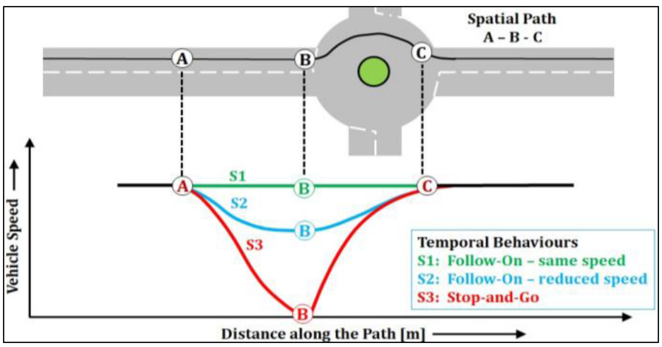


Fig. 2. Vehicle temporal behaviours at intersection.

A. The Behaviour Planning Concept

Naturalistic behaviour planning for an autonomous vehicle as defined in this work is an effort to imitate human-like motion behaviours while staying within the bounds of safe driving. The vehicle behaviours in this work are represented as consisting of two parts, the "spatial" which describes how the vehicle manoeuvres in space, and the "temporal" which describes the speed of the vehicle in the manoeuvres. The spatial part of the behaviour planning for a non-holonomic ground vehicle allows it to execute manoeuvres in space of the type "turning-left", "turning-right", "following" a straight/curved road etc. A planned path for an autonomous vehicle is therefore made up of a series of successive spatial behaviours that connect the vehicle start point to its desired destination, as shown in Fig. 1.

The temporal part of the behaviours involves a combination of the operational motions such as "acceleration", "cruising", "deceleration" and "stopping", enabling the vehicle to travel along a planned spatial path. For example, a temporal behaviour at an intersection can be a combination of deceleration-cruising-acceleration, or deceleration-stopping-acceleration etc. The choice of the temporal behaviour is highly influenced by the dynamics of the real-world environment. Fig. 2 shows three illustrative temporal behaviours for vehicle motion, i.e., "Follow-On" at the same speed, "Follow-On" at reduced speeds and "Stop-n-Go" motion.

The behaviour chosen by the vehicle to execute in a scenario determines whether its motion will be safe, efficient, comfortable etc. The temporal behaviours that take the vehicle on the path of other road users increase the risk of collision and are considered unsafe. The choice of temporal behaviours that involve frequent stopping even when opportunities exist to continue the motion can lead to increased travel times and can result in traffic congestion. Temporal behaviours involving rapid acceleration/deceleration, or travelling at high speed on curved roads can affect driving comfort. For successful autonomous navigation planning, vehicle safety is the primary requirement, and within the safety envelope, the behaviours that give optimal results on the chosen set of objectives such as driving efficiency, driving comfort etc., should be planned for autonomous vehicle motion.

B. Related Work

In the last couple of decades, autonomous vehicle trajectory planning efforts as discussed in Paden *et al.* [19] and Rodrigues *et al.* [20] have generally focused their efforts on firstly finding an optimal and safe spatial manoeuvers and then using a rule-based speed assignments to form a target trajectory that is evaluated for collision avoidance. These approaches, designed with a predefined rate of acceleration and deceleration are not effective for highly interactive environments with potential conflicts such as in intersection scenarios, where the vehicle does not always have the right-of-way/priority of motion. In such scenarios with potential conflicts, the manoeuvrable space for the vehicle motion is also highly dynamic, limiting the vehicles motion affordances. The rule-based speed planning approaches also put the responsibility of maintaining driving comfort on the motion controller, resulting in the motion controller having to define additional constraints on the vehicle motion. These constraints on the motion controller can sometimes significantly affect the motion controller's ability to successfully execute the planned motion behaviour plan, which is a critical safety concern. The vehicle motion in different road scenarios is also governed by the road geometry, i.e., curvy roads force the driver to slow down the vehicle to reduce the driving discomfort caused by increasing lateral accelerations. Gu and Dolan [21], proposed a geometry based speed planning approach in which a reference path was generated for the autonomous vehicle by combining the smooth and peak-value-reduced curvature and a parameterized speed model that was fitted from human driving data. While this was a step towards achieving the human-like naturalistic driving behaviours, the reference speed model used in their work was solely built on the geometric nature of the reference path and ignored other factors such as the motion of other actors and their interaction. Dong *et al*. [22], proposed a combined behaviour planning and trajectory planning method, where sampled trajectories were grouped by topological properties in the spatial-temporal domain to create different high-level manoeuvres patterns. This method has some similarities to our approach, wherein it combines the behaviour planning and trajectory planning to improve planning coherency and scalability, however, it currently lacks the reasoning capability required for negotiating interaction-based scenarios. Apart from the road geometry that constraint the maximum speed possible at each section of the scenario, the motion of the vehicle is also influenced by the traffic rules including motion priority among the vehicles at interaction-based scenarios such as crossroads, roundabouts etc. De Beaucorps *et al*. [23], developed a temporal speed planning approach for crossroad intersection scenario using the behaviour patterns learned from human drivers in a simulator experiment. The speed profiles from a crossroads intersection scenario were extracted to develop temporal behaviour plans using k-means clustering technique. As the clustered profiles were directly used in planning without real-time adaptations capability, this made them effective only for the specific type of intersection scenario in which the data was recorded. In addition, their approach also did not account for driving comfort, and the behaviour choices were limited to the number of speed clusters generated from data. Wei *et al*. [24], proposed a cooperative merging method for highway ramp merging using learned behaviour patterns of human driving. While this method simplifies the merging decision-making problem that is crucial for highly dynamic scenarios, the approach in the present form suits well for less ambiguous scenarios such as highway, where other actor's motion are generally predictable, which is not the case with intersections. Gindele *et al*. [25] proposed a tactical decision-making approach using continuous Partially Observable Markov Decision Process (POMDP), that based its autonomous vehicle behaviour selection on the predicted motion of other actors. Sefati *et al.* [26] proposed another tactical decision-making approach for autonomous vehicle behaviour selection using POMDP, that incorporated the uncertainty estimation. While both the above-mentioned approaches described a good decision-making approach for autonomous vehicle behaviour selection, they were not complemented by adaptive temporal behaviour plans that are critical for achieving motion efficiency and driving comfort. Successful autonomous vehicle navigation in dynamic, unpredictable and ambiguous real-world scenarios such as non-signalised roundabouts requires firstly the ability to predict the scenario evolution using contextual information and secondly the ability to plan adaptive temporal motion behaviour that leads to the autonomous vehicle achieving safe motion, driving efficiency and acceptable driving comfort. To achieve the above-mentioned objectives, a novel behaviour planning approach was developed called Adaptive Tactical Behaviour Planner (ATBP), which combines an adaptive, context-based dynamic temporal behaviour candidate generation with tactical decision-making ability to create adaptable behaviour plans. The ATBP algorithm development also involved the design and running of a human driving experiment on a simulator to collect naturalistic driving behaviour patterns to aid the design of adaptive temporal behaviour generation algorithm. The work presented in this paper is the second phase of a two-phase research project dedicated to the development of human-like behaviour planning approaches. In the first phase of the ATBP algorithm development presented in Rodrigues *et al.* [27], the naturalistic driving behaviours were learned from human drivers navigating different dynamic variations of the non-signalised roundabout scenarios on a desktop simulator. The learned patterns were later used to design the temporal candidate behaviours for both the "Follow-On" and "Stop-n-Go" as a three-part temporal behaviour profile using the Bezier curve method. A risk-aware multi-objective tactical decision-making algorithm was then used to select the optimal candidate temporal behaviour for the vehicle to execute during the autonomous navigation of the non-signalised roundabout. In this work it was demonstrated that the behaviour planner performed better than the human drivers on the desired objectives of safety (no collisions), drive efficiency (reduced travel times) and drive comfort (slower average speed in curves). The experiment, however, had a limited sample size of 10 human driving participants. Other limitations of the first phase include a low-fidelity vehicle model and limited vehicle motion feedback to the driver (only a visual), resulting in some driver behaviours that were not representative, limiting the useful behaviour dataset. In the phase-II of the ATBP development, greater emphasis was laid on improving both the driving environment (improved vehicle model and motion feedback) and also the participant number to enable collection of a wide and more realistic representation of naturalistic human driving behaviours. The ATBP algorithm developed in the phase-I was improved to incorporate the "Situational Awareness" and "Behaviour Prediction" functions which were integrated according to the behaviour planning framework designed in previous work [20]. The structure for the rest of this paper is as follows: Section II describes the ATBP algorithm design. In Section III the details of the human driving simulator experiment design and its running procedure are given. Section IV gives the analysis of human driving behaviours extracted from the experiment. Section V gives the description of the ATBP algorithm implementation. Section VI contains the performance analysis of the ATBP algorithm and discussion of the results. Finally, in Section VII the research work presented in the paper is summarised with appropriate conclusions.

II. Adaptive Tactical Behaviour Planner

A non-signalised roundabout is a highly dynamic environment where the behaviours of other road users can massively influence the autonomous manoeuvre planning. As the behaviours of actors in roundabout scenarios can change quickly and are difficult to predict accurately for long time horizons, the behaviour planning for an autonomous vehicle needs to be adaptable. Roundabouts can have different shapes and sizes and when combined with the variation in motion behaviours of other road users, it results in a dynamically changing drivable space. Such changing drivable space affects the motion affordances of the autonomous vehicle, limiting the motion behaviours possible in the scenario. At non-signalised roundabouts, the vehicles decision to merge is not governed by a centralised controller, and the actors have to merge into the roundabout according to the availability of gaps and their individual interpretation of priority to merge. Successful autonomous motion planning in such environments requires the ability to generate multiple behaviour plans and a tactical decision-making algorithm to select the optimal behaviour according to the existing dynamic situation. Generating multiple behaviour plans enables the vehicle to switch to a different behaviour if the changing environmental dynamics make the currently selected behaviour unusable. It can also ensure that the autonomous vehicle will always have a feasible future motion plan, thus avoiding unnecessary stops when opportunities exist to continue its motion. A tactical decision-making algorithm is required to enable the autonomous vehicle to select the best motion behaviour to execute at every iteration of the planner, as the changes in the environment can alter the importance of the design objectives (drive comfort, motion efficiency etc.). The ATBP combines an affordance-based naturalistic behaviour candidates generation with a risk-aware adaptive tactical decision-making to enable an autonomous vehicle to navigate highly dynamic, interaction-based scenarios safely, efficiently and with acceptable driving comfort. The concepts used in the design and implementation of the ATBP were first discussed in our publication [20], and the phase-I implementation of the novel Adaptive Tactical Behaviour Planner was illustrated in our publication [28]. The focus of phase-II development was only on the temporal behaviour planning, and the spatial behaviours are assumed to be fixed and known. The three functions of the ATBP algorithm, i.e., Situational Awareness, Behaviour Prediction and Behaviour Selection are, therefore, discussed in the context of temporal behaviour planning.

A. Situation Awareness

Situational Awareness (SA) is a term first defined by Endsley [29] as a combination of environment perception in time/space, understanding their meaning, and their subsequent projection in time. In our work, we attempt to develop an autonomous planning system that can mimic expert human driver's ability of decision-making and manoeuvre planning. In this regards the Situation Awareness represents the process by which the ATBP algorithm abstracts only the relevant information from the dynamic scenario to gain the necessary understanding needed to make informed behaviour choices. It is important to note that SA implementation does not replace the world representation map, which is an essential perception system activity of collating the sensed world data into a usable map of the vehicle surroundings. The SA algorithm implemented in this work firstly entails estimating the motion state (position, heading, speed etc.) for the actors of interest within the roundabout and those approaching from other directions. The actors of interest are those that are identified to be in potential conflict with the future motion plan of the subject vehicle. The second part of the SA involves identifying the priority for actors approaching the roundabout according to the driving guidelines (which for the UK are defined by regulation 184-190 of the Highway Code [30]). These guidelines are defined to solve the conflict in the decision making when actors arrive from different entry points at roundabout entry at the same time. However, in real-world situations, the actors can arrive at different times and at different speeds and it is therefore left to the interpretation of the individual driver to determine its priority to merge. In ATBP algorithm the SA function calculates a decision variable called "Interpreted Priority" ($IPrty$), which is estimated for all actors approaching the intersection and also for the subject vehicle based on their time of arrival at the Give way line

$$IPrty = sort_{ascend}\left(alli\left(\,TTA_{GWL,i}\right)\right)$$
$$i = 1, 2 \ldots n$$

where, "$TTA_{GWL,i}$" is the predicted time to arrival of the actors at the Give way line and "n" is the number of actors. The "$IPrty$" estimate uses a sort function to arrange the drivers in the ascending order of priority. The $IPrty$ variable evaluated in this work is different from the priority rules defined by the Highway Code [30], only when the actor vehicle is approaching their respective Give way line. If the actor vehicle reaches the Give way line either before or at the same time as the subject vehicle, or has already entered the roundabout, the regulatory rules defined by the Highway Code are strictly followed, implying the actor vehicle on the right has priority.

B. The Behaviour Prediction

The Behaviour Prediction (BhvPrd) function predicts the intention of the identified critical actors that are potentially in conflict with the subject vehicle's future motion. The prediction is based on the actor vehicle's past and present motion state, its position in the scene and the existing scenario dynamics. Thus, an actor moving away from the roundabout or past the potential conflict zones is considered non-critical. In the present implementation of the BhvPrd module, the actor vehicle intention is deduced into one of the three possibilities: "Advancing" (where the actor vehicle was predicted to continue its motion without stopping at the roundabout), "Stopping" (where the actor vehicle was predicted to come to a stop at the Give way line) or "No Estimate". The prediction is performed by comparing the actor's current behaviour to the average temporal behaviour profiles for "Follow-On" and "Stopping" obtained from the human driving experiment. The driving intention is then determined using the following rules

1) If the actor has priority and its motion matches closely with the average "Advancing" temporal behaviour then the actor's future intention is predicted as "Follow-On"
2) If the actor does not have priority and its motion matches closely with the average "Stopping" temporal behaviour, then the actor's future intention is predicted as "Stopping".
3) If the actor behaviour is mixed and does not conclusively match closely with either "Advancing" or "Stopping" behaviour, irrespective of priority the expected motion intention is interpreted as "No Estimate".

C. The Behaviour Selection

The Behaviour Selection (BhvSel) function involves two subfunctions, the generation of the temporal behaviour candidates and the decision to select a tactically optimal behaviour to execute. These two BhvSel functions are discussed below.

1) Temporal Candidate Generation: The temporal behaviours of the human drivers during a roundabout navigation are highly dependent on their manoeuvre choice. If an actor chooses to continue without stopping at the Give way line, then its speed profile at the roundabout results in a non-zero speed and continuous behaviour. On the other hand, if the driver decides to stop to yield to an oncoming actor before proceeding to merge after the actor vehicle, the navigation is in two discontinuous motion behaviours; one to bring the vehicle to a stop and the other to drive off from the stopped position. These two distinct behaviour types were termed as "Follow-On" and "Stop-n-Go" respectively in the phase-I ATBP algorithm development work [28]. A 3-part temporal behaviour profile construction used in

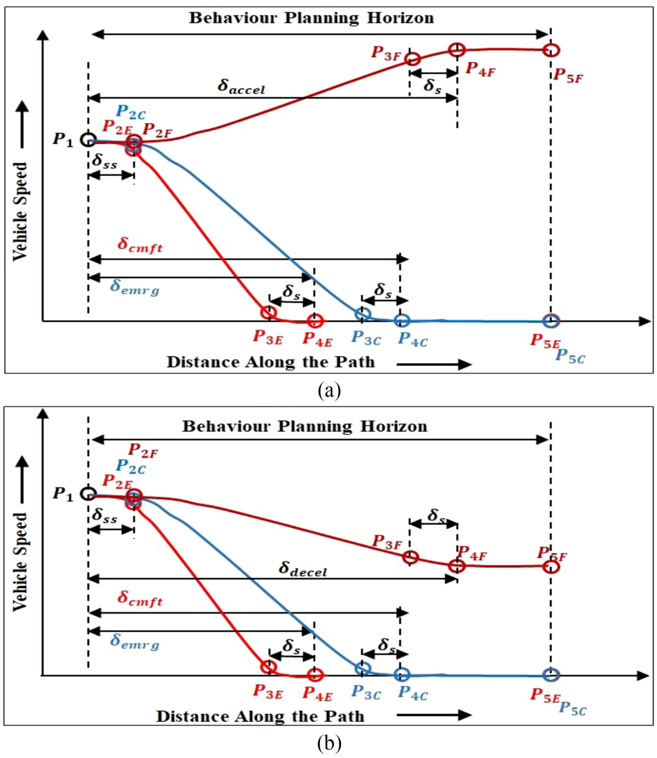


Fig. 3. Temporal behaviour extrema. (a) Acceleration. (b) Deceleration.

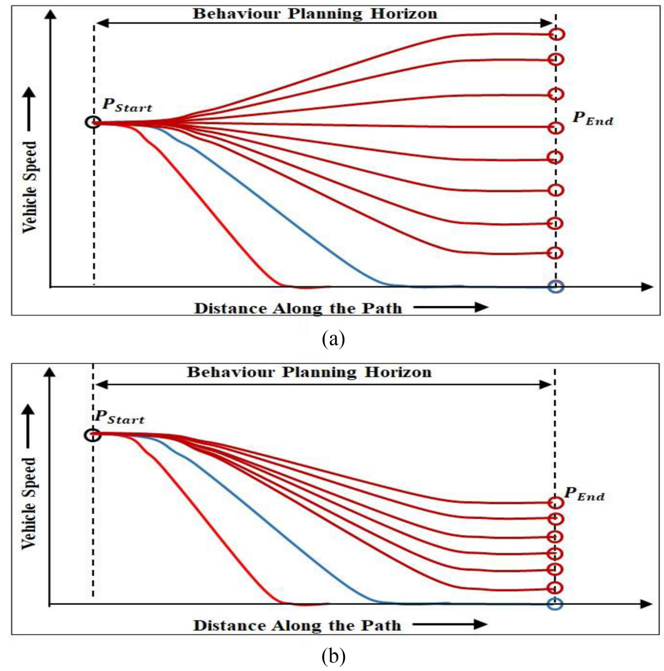


Fig. 4. Generated temporal behaviour candidates. (a) Acceleration. (b) Deceleration.

phase-I was found to be limited only to scenarios that had the possibility to stop. Due to the specific nature of the Stop-n-Go profile construction, it was also not directly applicable to other interaction-based scenarios such as overtaking, lane change etc. In this phase-II ATBP algorithm development, we decided to use a 2-part temporal behaviour construction in the generation of candidate's behaviours, to go from the current vehicle state to just another state in the future. As interaction scenarios can sometimes present emergency situations, where the other actors deviate significantly from the predicted behaviours, an additional behaviour profile for "emergency stop" was also added to give the vehicle the possibility to safely stop. Therefore, in total three behaviour profiles were constructed using the Bezier curve method, the two behaviour affordance extrema ("Follow-On" and "Comfort Stop") and the third for Emergency Stop. Bezier curve method was chosen for speed profile construction as it provides the flexibility of defining the individual control points to create a smooth, piece-wise continuous temporal profile, whose shape and gradients can be governed through the definition of the control points. The method avoids the problem of high-order polynomials and achieves continuously differentiable connections between the control points resulting in smooth trajectory profiles, which are easily tractable with the motion controller. The constructions of the speed profile for the situations of 'acceleration' and 'deceleration' are shown in Fig. 3(a) and Fig. 3(b) respectively. The control points suffixed by *"F"* are for "Follow-On" and *"C"* and *"E"* are for comfort and emergency stop temporal profiles respectively. The parameter "δ_{SS}" is the steady state parameter used for creating a smoother transition between successive temporal behaviour plans. Parameters "δ_{cmft}" and "δ_{emrg}" are the stopping distances for comfort-stop and emergency-stop respectively and are a function of the vehicle motion capability.

For the "Follow-On" temporal behaviour, the upper bound is influenced by the regulatory maximum speed. Therefore if the vehicle is currently at a lower speed than the regulatory speed, the control points that govern the shape of the upper extrema and the distance "δ_{accel}" of the control point P_{4F} are calculated accounting for the maximum acceleration the vehicle can achieve and similarly "δ_{decel}" for deceleration. The parameter "δ_s" is the calibrated profile shape parameter, which is estimated from human driving data for intersection scenarios. To generate naturalistic behaviour profiles, the patterns from the human driving experiment are used to influence the control points selection. A vehicle cannot always maintain the regulatory speeds due to the presence of other actors and other environmental factors such as sharp/tight road curvature etc. The behaviour planner, therefore, takes the current speed of the vehicle as the starting point of the temporal behaviour profile and creates affordance-based motion candidate profiles within the "Follow-On" and Comfort "Stop" profile envelope. The intermediate candidate profiles within this affordance envelope are generated using an interpolation method, as depicted in Fig. 4(a) and Fig. 4(b) respectively.

2) Risk-Aware Tactical Decision-Making: A decision-making algorithm was required for the ATBP to choose the optimum motion behaviours that were "Safe", "efficient" and result in an acceptable "motion comfort". In the ATBP, a multi-objective optimisation approach was used to continuously select a behaviour to execute from all affordable safe temporal motion behaviour candidates that optimised the objectives of driving efficiency and drive comfort. The safe candidate profile set was

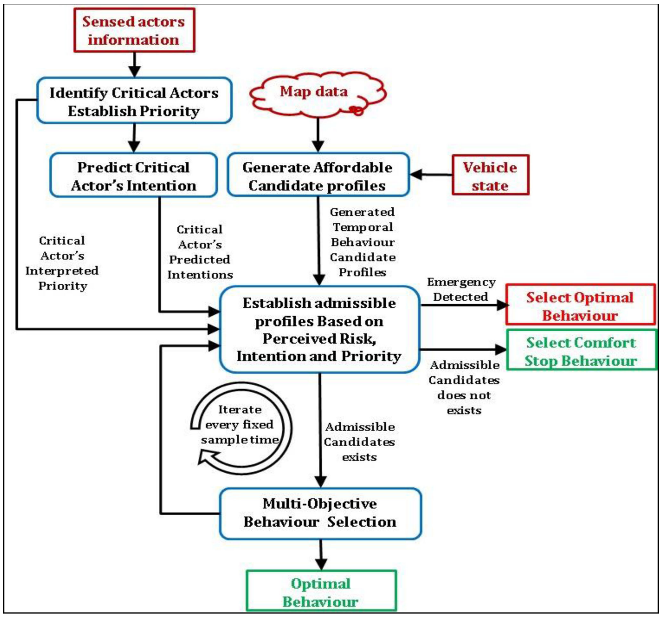


Fig. 5. Risk aware tactical decision-making algorithm.

first established from the affordance behaviour candidate set by calculating the Time-To-Give-way-line $(TTGwl)$ parameters for each candidate and comparing it against the actor vehicles in potential conflict with the subject vehicle motion on those candidates. The behaviour selection decision-making algorithm then 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 estimating the $TTGwl$ using the constant speed projection method.

$$TTYl_{act} = d_{path,act} * v_{act}$$

where, $d_{path,act}$ is the distance of the actor along its path to the "Give way line", and v_{act} is the estimated velocity of the actor. The same parameter is then calculated for every behaviour candidates of the subject vehicle (i.e., $TTGwl_{sub,i}$) to establish the set of candidate profile that result in non-conflicting motion. The overall behaviour selection function to choose the optimal behaviour from the safe candidate behaviour set was then formulated as an objective function,'Q', which was minimized to find the optimal candidate with the lowest penalty.

$$\min_{all,candidates} Q_{cand} = a * CI_{lat} + b * CI_{long} + c * WTI$$

where, 'CI' and 'WTI', are comfort index and the waiting time index (efficiency index) respectively. Coefficients 'a', 'b' and 'c' are tuning parameters to weight the objectives of "Lateral comfort", "Longitudinal comfort" and "Waiting Time" at Give way line based on a design preference. With the defined indexes and the objective function, the flow of the ATBP algorithm for selecting the optimal behaviours for a roundabout navigation is depicted in Fig. 5.

In this work, the algorithm was designed to recalculate the optimal behaviour plan every 200 ms, and therefore it iteratively selected the best tactical temporal behaviour, giving the autonomous vehicle the ability to take all merging opportunities.

Fig. 6. The simulator driving environment set-up.

III. The Human Driving Experiment

The objective of the simulator experiment was to gain insight into naturalistic human driver's temporal behaviours during the navigation of a non-signalised roundabout. Learning from the limitations of the phase-I of this research work, this experiment was designed with the aim of extracting more representative human driving behaviour profiles. Three specific improvements were made in this driving simulator experiment, which included (a) An improved driving environment (high-fidelity vehicle model, real-world calibrated driver controls and improved motion feedback cues), (b) Increased navigation scenario sets (with variation in both the static and dynamic environment), and (c) A larger and more representative human driving participant sample. These improvements and the analysis are described in this section.

A. The Driving Environment

The driving simulator was built using PreScan [31], an environment modelling toolkit for creating representative real-world driving scenarios. The background models were developed in Matlab Simulink and a multicore PC was used for high computation capability. Powered by a high-capacity graphics card, the visualisation output from PreScan was projected on a white background through a multi-projector set-up, as depicted in Fig. 6. The driving run consisted of 3 single-lane 4-exit non-signalised roundabouts of different sizes. The "subject vehicle" driven by the human driver and the "actor vehicle" controlled by the autonomous settings approached the intersection from two different entry points.

Fig. 7 depicts the bird's eye view of the three roundabouts of radius 20 meters, 25 meters and 15 meters respectively. The roundabouts were connected with a long straight approach road, allowing the drivers enough driving length to get to the desired speeds before a roundabout was in sight. Within each roundabout, a maximum travel speed was suggested to the drivers as an indicative speed for driving stability and comfort. The speed that the drivers actually maintain at the roundabout, however, was according to their natural driving.

B. The Scenario Dynamics

The combination of the subject vehicle regulatory speed variations and the different speed settings for the actor vehicle created

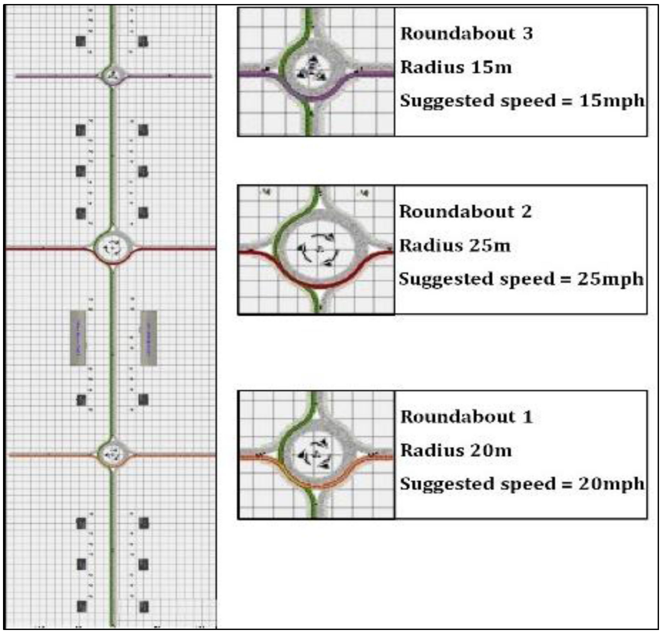


Fig. 7. The scenarios for the human driving experiment.

TABLE I
SCENARIO SETTINGS FOR HUMAN DRIVING EXPERIMENT

Scenario ID	Subject Vehicle	Actor Vehicle
SA1	Reg Speed = 25 mph	Set Speed = 0mph (no vehicle)
SA2	Reg Speed = 25 mph	Set Speed = 20 mph
SA3	Reg Speed = 25 mph	Set Speed = 30 mph
SA4	Reg Speed = 30 mph	Set Speed = 0 mph (no vehicle)
SA5	Reg Speed = 30 mph	Set Speed = 25 mph
SA6	Reg Speed = 30 mph	Set Speed = 35 mph
SA7	Reg Speed = 40 mph	Set Speed = 0 mph(no vehicle)
SA8	Reg Speed = 40 mph	Set Speed = 35 mph
SA9	Reg Speed = 40 mph	Set Speed = 45 mph

nine dynamically different driving scenarios at each of the three non-signalised roundabouts. This resulted in 27 different scenarios for each human driver participant to navigate. The actor vehicle motion was controlled by automated with a pure-pursuit based lateral control and a PID based longitudinal control and had a dynamic vehicle model. The speed settings for the nine scenarios are shown in Table I. The target plan for the human driver in each scenario was to achieve the regulatory speed when on the straight road and then navigate the roundabout according to the existing dynamic scenario and to their natural driving style.

The priority rule defined in the Highway code [30] is designed to solve the conflict situation only, and it was shown in phase-I that human drivers tend to make the decision on various other factors including the actor vehicles approach behaviour, the size and shape of the roundabout etc. The human driver's decision to merge into the roundabout before the actor vehicle or to stop at the Give way line to allow the actor vehicle to pass before it was a result of the individual's ability to assess the situation and make a decision on its behaviour. The order of the scenarios presented to drivers was randomized, thus the driver had no prior knowledge of the actor vehicle behaviour. This randomization

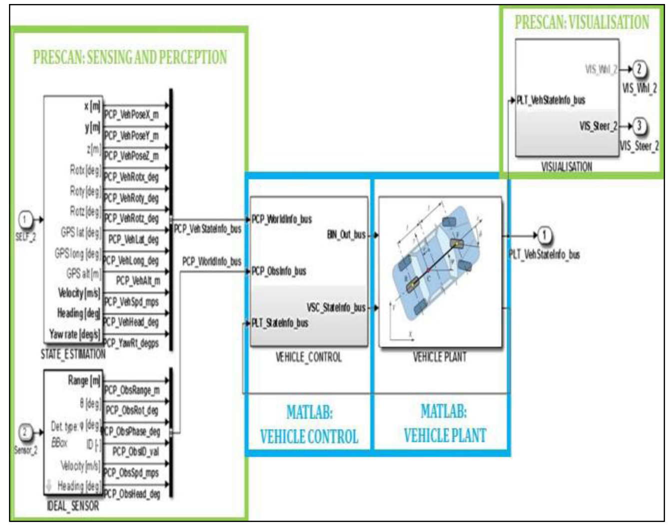


Fig. 8. Tata HEXA vehicle model designed in Matlab Simulink [32].

TABLE II
TATA HEXA VEHICLE SPECIFICATIONS

Particulars	Specification
Weight	2,280kg (kerb).
l, w, h	4.788m, 1.903m, 1.791m
Max power: PS@RPM	156PS@4000
Max torque: Nm@RPM	400Nm@1700-2700
Wheelbase	2.850m
Turning Circle Radius	5.75m

of the scenarios eliminated the possibility of the human drivers pre-meditating their decision and therefore only adapting their behaviours based on the existing scenario.

C. Vehicle Model

A vehicle plant model was necessary to provide the human driver with a realistic feedback of the vehicle motion to their control inputs. The schematic of the vehicle model built in Matlab Simulink and integrated into PreScan is shown in Fig. 8. More details on the vehicle model are in our previous publication [32].

A dynamic bicycle modelling approach [23] was used to represent the TATA HEXA vehicle whose behaviour was co-related with real-world driving data. A brief list of specifications of the TATA Hexa vehicle is shown in Table II.

D. Vehicle Control

The vehicle control is an important aspect of realistic data acquisition of naturalistic human driver motion behaviours. In the simulator, the drive controls were set up using a gaming unit. The drive pedal feel was calibrated with the tuning of the stiffness, damping and spring coefficients to achieve realistic force feedback.

1) The Lateral Control: Human drivers show variability in the lateral control of the vehicle, which can lead to differences in the travelled distance, and 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 to control the vehicle's longitudinal motion.

2) The Longitudinal Control: The driver's accelerator pedal demand was processed through the vehicle's powertrain model into traction force. The accelerator pedal and brake pedal latency were estimated from real-world data of HEXA vehicle and incorporated into the drive-by-wire model. Familiarity with the vehicle also plays a crucial role in drivers exhibiting naturalistic behaviours, and therefore before any behaviours were recorded, the drivers were given multiple runs to familiarise themselves with the driving controls and the motion feedback cues in the experiment.

E. Participant Selection

As a mandatory requirement, only drivers having the full UK driving licence and only drivers with a minimum of at least 1-year driving experience in the UK were considered. The plan for the phase-II experiment was to get a wider representation of the participants in the categories of age groups, gender etc., than the one of the phase-I experiment. As this study's interest lies in understanding human drivers behaviour planning and decision-making, it was desirable to have some representation of participants who have undergone advanced driver training. Another desirable attribute used during the search for potential participants was their familiarity to the video gaming controls, and/or vehicle testing experience, as that would mean lesser time to get used to the driver controls. Another improvement over the phase-I study was to have a greater spread of the participants driving experiences in the UK. The participant's distribution in the categories of gender, age, driving experience, advanced driving skill, vehicle testing experience and video gaming experience are shown in Fig. 9.

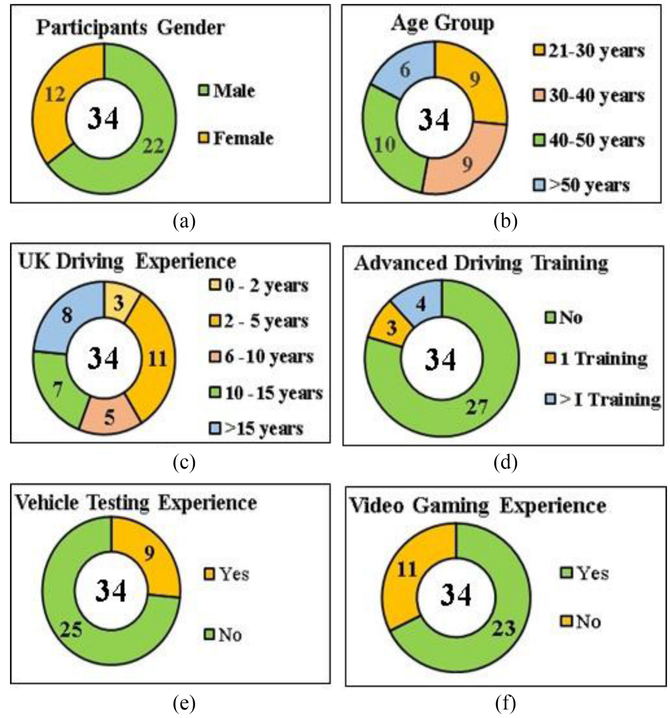


Fig. 9. The participant distribution as per (a) gender, (b) age group, (c) UK driving experience, (d) advanced driving training, (e) vehicle testing experience, (f) video gaming experience.

IV. Analysis of Human Temporal Behaviours

A. Key Findings From the Temporal Behaviour Profiles

In the rest of the paper, the three roundabouts are termed R15, R20 and R25 for roundabouts of radius 15m, 20 m and 25 m respectively. The temporal behaviour profiles for all the human driver participants at each roundabout for the three regulatory speeds are shown in Fig. 10, Fig. 11 and Fig. 12 respectively.

The key observations in the human driver's motion behaviours are broadly summarised as follows:

1) Yielding without stopping: Fig. 10, Fig. 11 and Fig. 12 show that some drivers slowed down considerably at a distance of up to 25 meters before the Give way line to yield for the actor vehicle. This behaviour of slowing down enables the drivers to continue the navigation without stopping after the actor vehicle has passed.

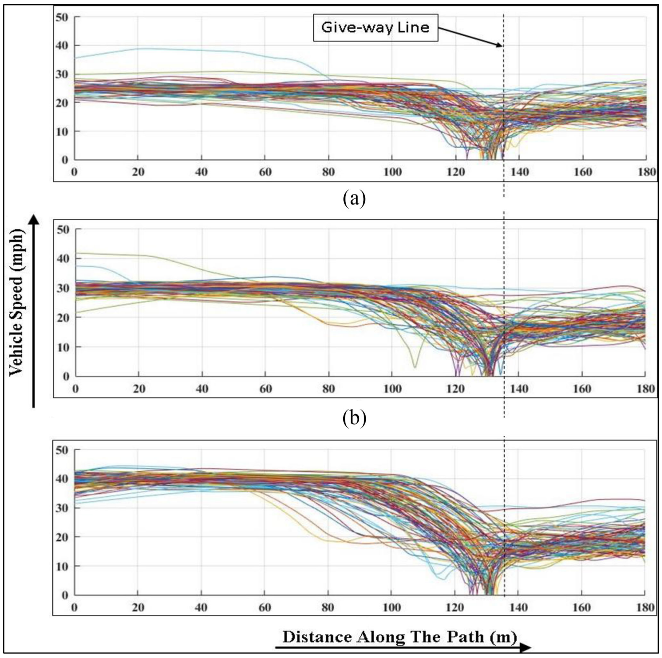
2) Stopping away from the Give way line: Some drivers stopped up to 10 meters away from the Give way line. This shows that they did not utilize the full length of the available approach path; this difference in behaviour can potentially create confusion about the vehicle motion intention.

3) High speed within the curves: Some human drivers carried the higher approach speed into the roundabouts, especially when trying to merge ahead of an oncoming actor vehicle. This can be established from the closeness of the average navigation time at the three roundabouts. Fig. 13 shows that the average navigation time of some drivers at all the roundabouts was very close, even though the travelling distances are larger in the bigger roundabouts. The higher speeds within the roundabout suggest that the drivers accepted the "local" discomfort in order to reduce the time spent at the roundabout.

4) Manoeuvres Choice: The human driver's temporal behaviour profile's variations along the path distance in Fig. 10, Fig. 11 and Fig. 12 indicate that they make the decision to either Follow-On or Stop, at a considerable distance before reaching the Give way line. This implies that human drivers use some prediction of the other actor's motion to make the manoeuvre choice and therefore do not always come to a stop at the Give way line.

B. Descriptive Statistical Analysis

The temporal behaviour profiles of the human drivers were analysed using descriptive statistical measures. Three types of behaviour performance indicators were extracted from the data as described below.



(c)

Fig. 10. Temporal behaviour profiles for R15. (a) Regulatory speed of 25 mph. (b) Regulatory speed of 30 mph. (c) Regulatory speed of 40 mph.

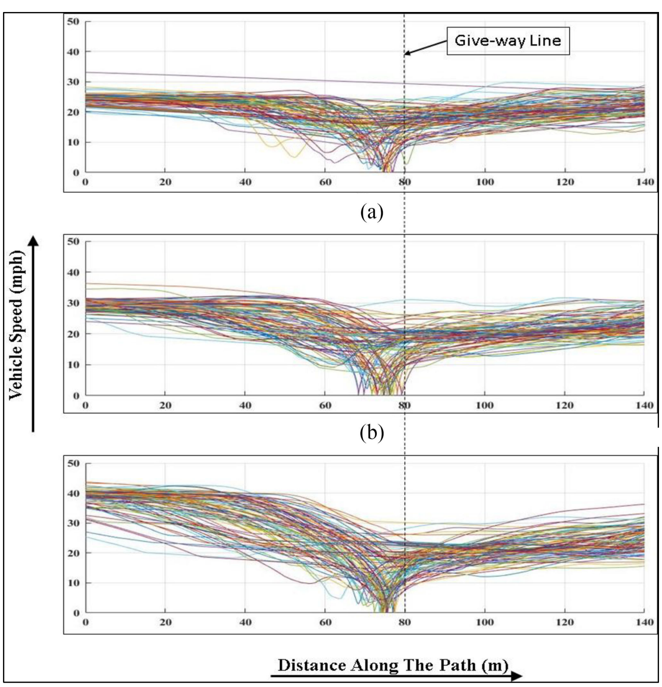


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Fig. 11. Temporal behaviour profiles for R20. (a) Regulatory speed of 25 mph. (b) Regulatory speed of 30 mph. (c) Regulatory speed of 40 mph.

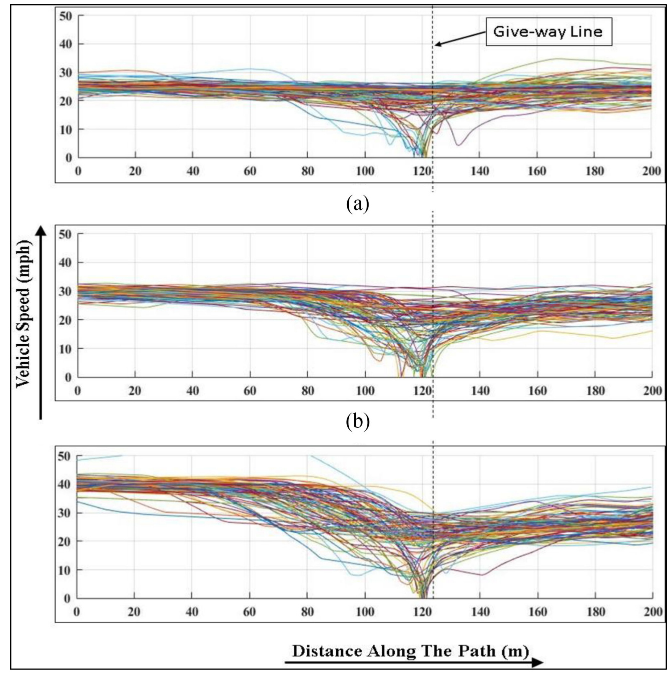

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Fig. 12. Temporal behaviour profiles for R25. (a) Regulatory speed of 25 mph. (b) Regulatory speed of 30 mph. (c) Regulatory speed of 40 mph.

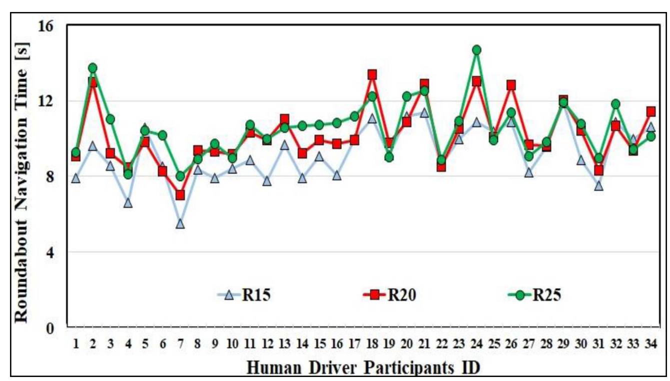


Fig. 13. Average time for roundabout navigation.

1) *Situation Awareness and Risk Assessment Performance:* To establish the human driver's situational awareness capability and their risk assessment performance, two indicative parameters were extracted from data: "Number of Collisions" and "Number of Near Misses". In this work, we considered collision as an event when the subject vehicle had a direct contact with the actor vehicle (i.e., either a front-on collision or on the side of the vehicle). Fig. 14(a) shows the number of collisions by the human drivers. A Near-Miss as described in this work is an event where the subject vehicle was driven by the human driver aggressively merged in front of the actor vehicle, leading to the actor vehicle either hitting the subject vehicle in a rear-end collision or coming within less than one car length of colliding with the subject vehicle. This is a type of event where the actor vehicle would have to slow down significantly from its normal course to accommodate the subject vehicle. The number of near-misses for the human-driven participants is shown in Fig. 14(b).

2) *Behaviour Decision Efficiency Indicators:* Two type of descriptive decision quality indicators were extracted from the driving data, which enabled the evaluation and comparison of

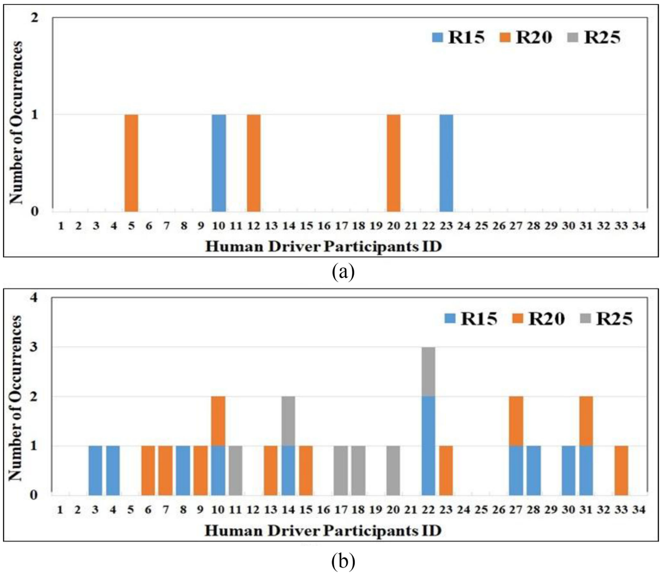


Fig. 14. Number of (a) collisions (b) near miss for individual human drivers.

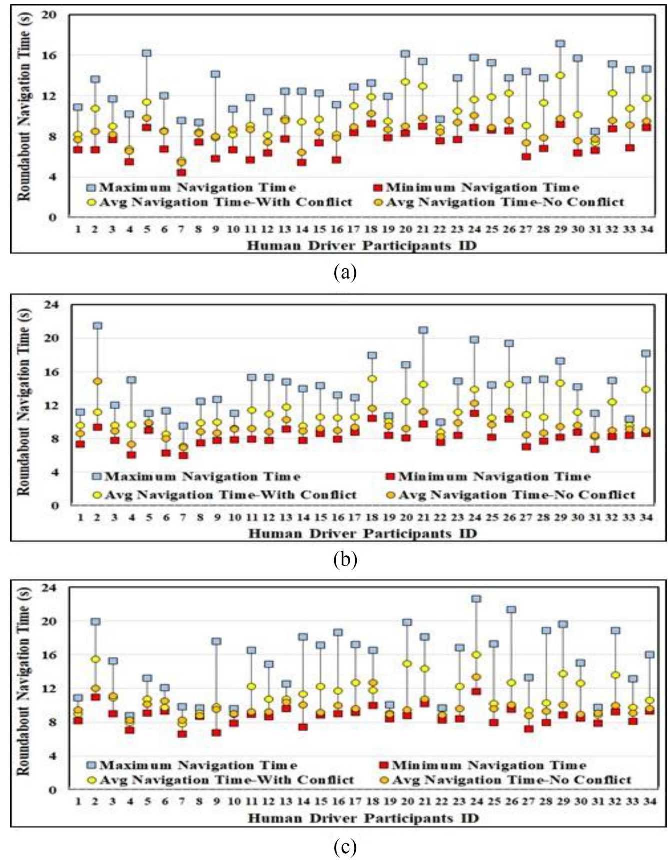


Fig. 15. Calculated navigation time for the human driver participants. (a) R15 roundabout. (b) R20 roundabout. (c) R25 roundabout.

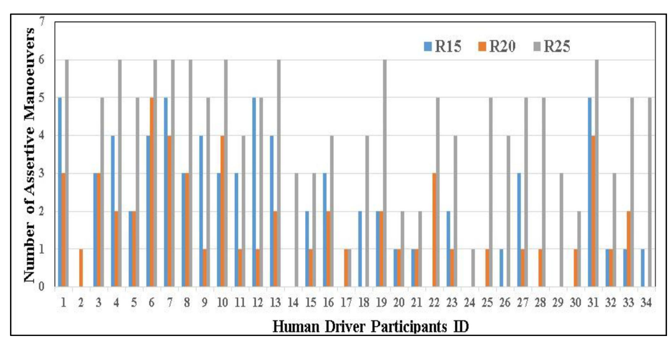


Fig. 16. Number of assertive passes for human drivers out of six scenarios.

the human driving efficiency in different dynamic roundabout scenarios. The first of these indicators is the set of human driver's navigation time parameters at the roundabout, as shown in Fig. 15.

The variation in the difference between the maximum and minimum navigation time among human drivers suggests that some drivers are more consistent with their performance than others. Higher navigation times also suggests a lack of tactical decision-making ability and directly affects the efficiency of the driving. The scenarios with the actor vehicle approaching the roundabout from the right of the subject vehicle represented the scenarios with conflict (due to the possibility of collision with the actor vehicle) and the ones without actor vehicle represented no-conflict scenarios. As the drivers were not informed beforehand about the presence or absence of the actor vehicle and had to make their behaviour decisions based on what they saw in the scenario, a smaller difference in average time between conflict and non-conflict scenario suggests advanced driving behaviours.

The second type of efficiency indicator is the number of "assertive passes" by the human drivers. Assertive passes refer to the successful merges before the actor vehicle, which are shown in Fig. 16. Non-assertive passes/defensive passes are motion behaviour where the vehicle navigated the roundabout after the actor vehicle has passed.

Fig. 16 shows that at the larger roundabout (R25), drivers show more tendency to be assertive, as the larger roundabout allows higher speeds due to its reduced curvature.

3) Manoeuvre Planning Quality Indicators: The third type of statistics obtained from the human driving data was the Manoeuvre Quality Indicators. The maximum longitudinal acceleration and maximum lateral acceleration were chosen as indicators of vehicle longitudinal and lateral drive comfort respectively, with higher acceleration /deceleration mean greater discomfort. Fig. 17(a) shows the vehicle maximum longitudinal acceleration for the human driver's motion behaviours at the three roundabouts. (Note: for plotting, the decelerations were also classed as accelerations). A maximum longitudinal acceleration of 0.4 g $(g = 9.8\ m/s^2)$ is generally accepted as a driving comfort threshold. However, as seen in Fig. 17(a), in the presence of the actor in a merging scenario, some drivers vehicle acceleration was considerably higher at the cost of driving comfort, in order to reduce waiting time. Fig. 17(b) shows the individual human driver's vehicle maximum lateral accelerations at the three roundabouts. The maximum lateral acceleration ranged between 0.3 g-0.8 g, indicating that some drivers were accepting higher lateral discomfort for short time periods. These levels of lateral acceleration seen in the

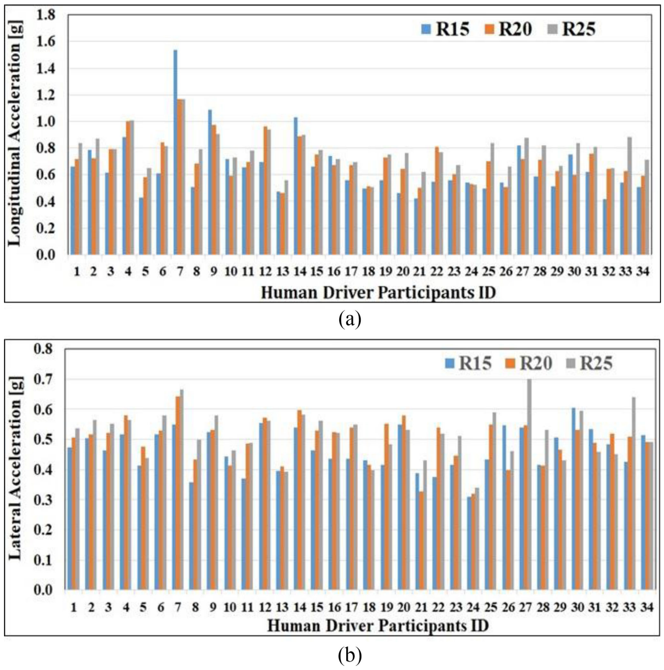


Fig. 17. Human driving participant's maximum. (a) Longitudinal acceleration. (b) Lateral acceleration.

roundabouts for short periods would be considered unacceptable for longer periods and on straight roads.

V. The Behaviour Planner Implementation

The parameters for the candidate generation algorithm were obtained by analysing the human driving data. The distance parameters for comfort-stop and emergency-stop were obtained using the relation,

$$\delta = 1.2 * v + \frac{v^2}{2 * a}$$

Here "v" is the current vehicle speed, the parameter "a" is the acceleration of the vehicle respectively. All the profiles from the human drivers were evaluated based on the three objectives for each scenario. Firstly, based on safety all the temporal profiles that had near-misses and collisions were removed, then based on the comfort thresholds all the behaviours that exceeded the comfort threshold were removed, and finally, from the remaining set, the behaviours that had the shortest travel times were selected as representative of expert driving behaviours. The parameters values for the ATBP deceleration and accelaeration distances as well as the shape parameter were established from the analysis of the expert behaviours. The planning horizon had to be greater then δ_{cmft} to ensure that the vehicle behaviour-planning horizon always contained a behaviour that could bring the vehicle to a comfortable stop. Therefore, a planning time horizon of 4 s was chosen for the candidate generation. The steady state parameter of $\delta_{SS} = 0.25$ m was used for smoothing the behaviour profiles at the start. All the temporal speed profiles from the human drivers were evaluated based on the three objectives for each scenario. Having established the parameters of the behaviour candidate generation, the pseudo-code for the ATBP algorithm is given below.

Algorithm: Adaptive Tactical Behaviour Planner.

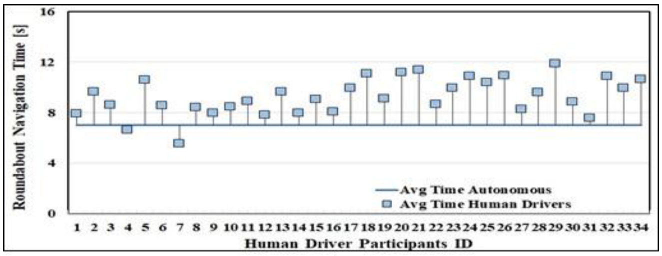
When approaching a roundabout

1. In the Situational Awareness function, establish the critical actor's whose predicted future motion is in potential conflict with that of the subject vehicle and establishes their Interpreted Priority.
2. In the Behaviour Prediction function establish the actor vehicle intention.
3. Using the state estimate of the critical actors in the scene estimate the '$TTGwl$'.
4. Estimate the candidate time gap as
   For all candidates 'i' and for all actors 'j'
   $TimeGap_{Yl} = TTGwl_{cand,i} - TTGw_{act,j}$
   Where i = 1, 2, 3 . . . ., n (n - number of candidates).
5. Find admissible candidates for the multi-objective tactical selection as
   a) If the actor vehicle predicted intention is "Advancing", establish if any of the candidate profiles for the subject vehicle give it priority over the actor vehicle. This is established by computing the Interpreted Priority for each candidate behaviours generated for the subject vehicle. Use all profiles that give the subject vehicle a safe time gap as admissible candidates for selection.
   b) If the actor vehicle predicted intention is "Advancing" and the Interpreted Priority of the subject vehicle is below the conflicting vehicle, find if there exist any feasible candidates with "post-time" gap greater than the safe gap.
   c) If the actor vehicle predicted intention is "Stop", use all "Advancing temporal behaviour candidates as admissible for selection."
      - The safe time gap chosen for this work is "1.5 sec".
      - "Pre-Time "and "Post-time" gaps are safe gaps for merging into the roundabout before and after the actor vehicle respectively.
6. Select the behaviour candidate among the admissible candidates with the minimum penalty index according to the defined objective function.
7. If none of the "Follow-On" candidates has time-gap greater than the safe gap, choose the "Stop candidate profile to come to a comfortable stop.

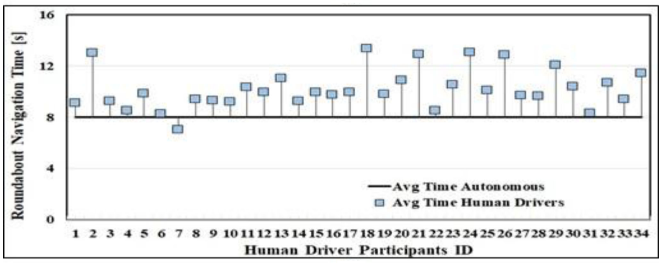
In case of an emergency, select the emergency stop temporal profile to enable the vehicle comes to a stop as soon as possible.

VI. Results And Discussion

1) Driving Efficiency: Fig. 18 shows that the autonomous vehicle outperformed most of the human driver participants on the criterion of "average navigation time". The driver with ID-7 managed to get a smaller average time than the autonomous vehicle in all roundabouts. The driver



(a)



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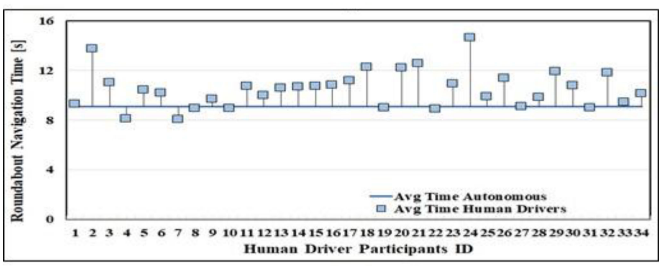
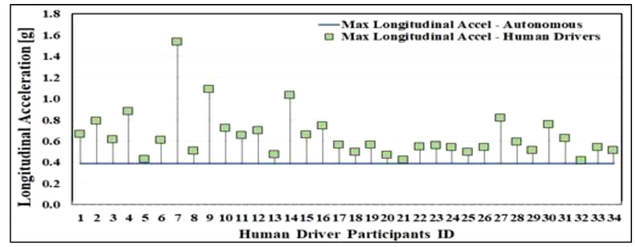


(c)

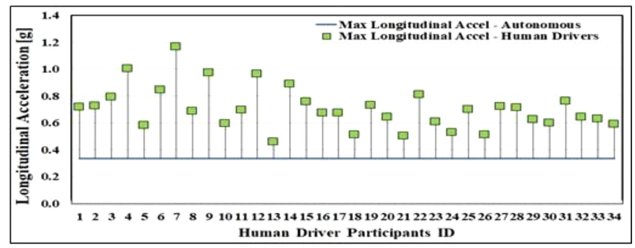
Fig. 18. ATBP vehicle "navigation time" comparison with human drivers at the roundabout (a) R15, (b) R20, and (c) R25.

with ID-4 also showed smaller average time than the autonomous vehicle in R15 and R25.

2) Driving Comfort-longitudinal: Fig. 19 shows that the autonomous vehicle had better control of the longitudinal acceleration and therefore better drive comfort. As the scenario consists of actors merging at roundabouts with the possibility of motion conflict, local longitudinal acceleration below 0.4 g was considered acceptable. Driver with ID-7 and ID-4, who performed well in reducing navigation time had acceleration levels (>1 g) which are considered unacceptable for passenger cars.
3) Driving Comfort-Lateral: Fig. 20 shows that most driver's maximum lateral acceleration for R15 was around 0.5 g while that for R20 and R25 were slightly on the higher side (by 0.2 g-0.4 g). These levels of lateral acceleration although local for a scenario like roundabouts, are still considered as above the acceptable thresholds for comfortable driving. The autonomous vehicle was able to maintain its acceleration within acceptable thresholds of 0.4 g at all the three roundabouts.
4) Decision-making: Fig. 21 shows that the autonomous vehicle completed the most successful assertive manoeuvres than all human drivers. It also did not have any collisions or near misses. This highlights the superior tactical decision-making ability of the ATBP algorithm.



(a)



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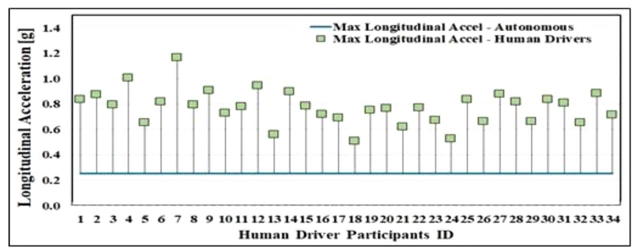

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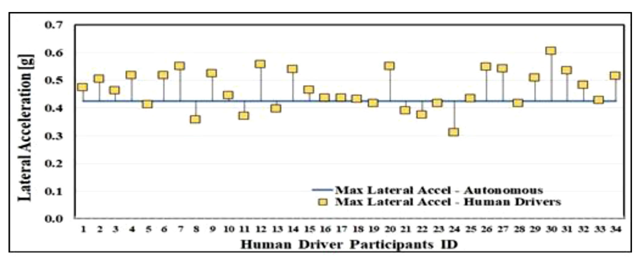
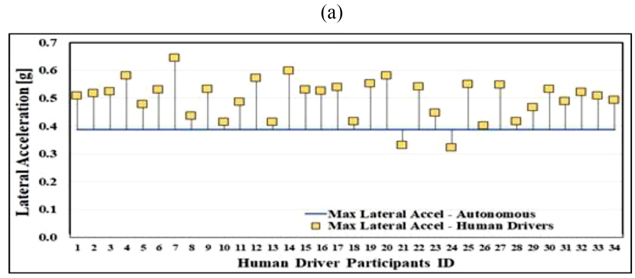
Fig. 19. ATBP vehicle "driving comfort index" comparison with human drivers – Longitudinal acceleration (a) R15, (b) R20, and (c) R25.



(a)



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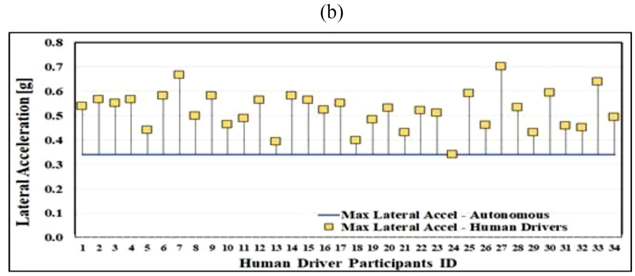

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Fig. 20. ATBP vehicle "driving comfort index" comparison with human drivers – Lateral acceleration (a) R15, (b) R20, and (c) R25.

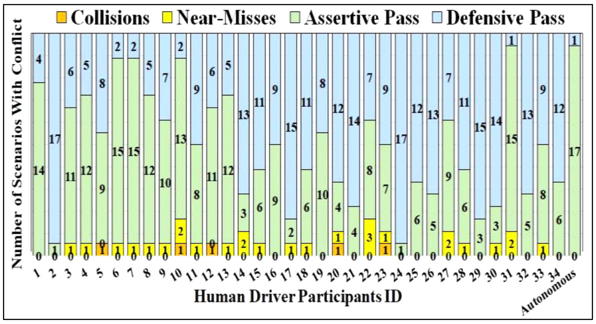

Fig. 21. ATBP vehicle "safety" performance indicators comparison with human drivers.

VII. Conclusion

This paper presented the phase-II development of a novel Adaptive Tactical Behaviour Planner for autonomous ground vehicle application, which can be summarised as follows

1) The designed ATBP algorithm combines the capabilities of naturalistic temporal behaviour generation with a tactical decision-making to generate human-like motion behaviour plans. This gives the autonomous vehicle the capability to navigate dynamic, interaction-based scenarios. The design, implementation and working of the ATBP algorithm were described in this paper with the application case of a non-signalised roundabout.
2) PreScan, an environment-modelling tool, was used to design the driving simulator experiment, generating a realistic driving scenario. Significant improvements were made in the motion feedback available to the human driver missing in phase-I development [28], by adding audio feedback cues (vehicle and road sound emulation) and visual feedback cues (life-sized vehicles projections).
3) Geometrically different sized roundabouts were used in this study to understand the variation in the behaviour planning and decision making of human drivers. These differently sized roundabouts, coupled with the variation in the actor behaviours enabled the creation of 27 dynamically different merging situation to analyse human driver motion behaviours.
4) A much-changed Adaptive Tactical Behaviour Planner implementation was described in this work using the learning from the phase-I implementation. In addition to the improving "Situational Awareness" and "Behaviour Prediction" functions, the temporal candidate profiles generation algorithm was also modified to make the algorithm applicable to other scenario types.
5) The behaviour selection decision-making function was improved from phase-I to include the "Interpreted Priority" and "Predicted Intention" estimates in the behaviour selection decision.
6) Comparing the overall performance against the three objectives of motion efficiency, motion comfort and motion safety, the autonomous vehicle with the ATBP algorithm outperformed all of the human driving participants from the experiment.
7) The absence of the haptic feedback plays an important part in human drivers accepting higher acceleration in simulation studies as compared to real-world driving. We plan to mitigate this limitation in future studies by either providing a haptic feedback or artificially limiting the vehicles accelerations.
8) Generally, pure naturalistic behaviours are difficult to be observed in simulation environments; however, it was chosen as the platform for acquiring human driving behaviour data for two main reasons. Firstly, it presented a cost-effective, risk-free solution, as there was no cost associated with a potential collision or a near miss. Secondly, in a simulation environment, the interaction scenarios were repeatable, allowing the possibility to observe and compare the driving behaviours of multiple drivers in exactly the same scenarios.
9) In the current study, the behaviour of the actor vehicle was automated, which made it easy for the prediction algorithm of the ATBP to provide crisp results on whether the vehicle was advancing/stopping. Therefore, in the current study, the capability of the behaviour prediction algorithm was not fully tested with scenarios where the actor vehicle changes its intention more than once during the approach. The behaviour prediction algorithm will be tested in the future to consider such cases.
10) A conflict of motion paths between merging actors in the absence of inter-vehicle communication is a critical challenge for autonomous vehicle planning systems. This work is, therefore, a step forward towards achieving autonomous navigation in interaction-based scenarios in the absence of direct inter-vehicle communication. It was shown that the ATBP algorithm performance was found to be better at all the objectives against human driver participants. The autonomous vehicle with the ATBP algorithm was found to be safer (i.e., "0" collisions, "0" near-misses) compared to 68% of the human driver participants who had one or more near misses or collision. It was more efficient, i.e., It had the most assertive passes than all human driver participants and the least average time spent at the roundabout compared to all but one participant. It was also found to have better driving comfort (combination of lateral and longitudinal) than all human driver participants. The next stage of the ATBP algorithm development is to test it in real-world environments.

Acknowledgment

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