# Adaptive Tactical Behaviour Planner for Autonomous Ground Vehicle

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***Abstract*— Success of autonomous vehicle to effectively replace a human driver depends on its ability to plan safe, efficient and usable paths in dynamically evolving traffic scenarios. This challenge gets more difficult when the autonomous vehicle has to drive through scenarios such as intersections that demand interactive behavior for successful navigation. The many autonomous vehicle demonstrations over the last few decades have highlighted the limitations in the current state of the art in path planning solutions. They have been found to result in inefficient and sometime unsafe behaviours when tackling interactively demanding scenarios. In this paper we review the current state of the art of path planning solutions, the individual planners and the associated methods for each planner. We then establish a gap in the path planning solutions by reviewing the methods against the objectives for successful path planning. A new adaptive tactical behaviour planner framework is then proposed to fill this gap. The behaviour planning framework is motivated by how expert human drivers plan their behaviours in interactive scenarios. Individual modules of the behaviour planner is then described with the description how it fits in the overall framework. Finally we discuss how this planner is expected to generate safe and efficient behaviors in complex dynamic traffic scenarios by considering a case of an un-signalised roundabout.**

***Keywords—Path Planning, Global Planner, Local Planner, Behaviour Planner, Situation Awarness, Dynamic Bayesean Network.***

## I. Introduction

The digital technology advancements in the 21st century has given new impetus to research the autonomous vehicle technology in the automotive sector. Autonomy has already been successfully demonstrated in indoor robotics, with the early interest mainly driven by academia and other robotics research institutions. However the aim of having vehicles that drive autonomously on public roads is now looking much closer to fulfilment. This change in perception has been brought about by considerable research effort by academia, industry and through government intervention over the last two decades [1],[2],[3],[4]. There have been many well publicised demonstrations of the autonomous ground vehicle technology, however it is important to note that they were carried out in limited risk or controlled environments. For instance the cars at the DARPA Urban Challenge (DUC) for example had a remote monitor and controller, which on many occasion avoided collision by remotely switching of the cars. Vislab Intercontinental Autonomous Challenge, had only simple autonomous functions such as following a vehicle ahead [2]. The Mercedes Berth drive [3] and Google driverless vehicles had human operators in them to intervene in times of failure or uncertain behaviour [4].

The control software that replaces a human operator in the autonomous vehicle has undergone steady evolution over the years. This software essentially consists of three main parts,

a. Perception - tasked with collating sensed information of the vehicle surroundings to form a world representation.
b. Path planning - tasked with generating a future path from the vehicles current location to its intended destination
c. Motion control - tasked with having to execute the planned path to reach the intended destination.

The schematic shown in Fig.1, encompasses the general format of the control software architecture derived from various published literature of autonomous ground vehicle control software implementations.

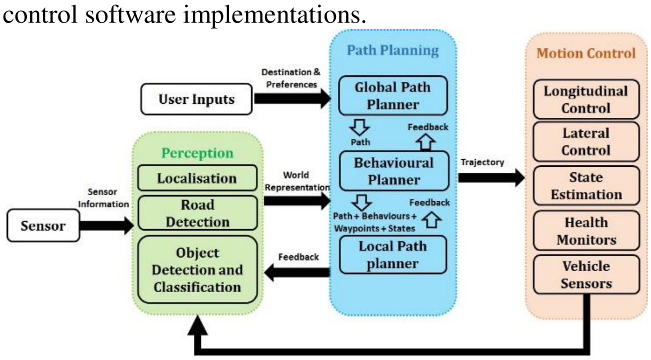


Fig. 1. Autonomous Control Software Architecture.

The advances in sensor technologies (camera, LIDAR, RADAR GPS etc.), has aided the research community to make significant progress in the area of world perception. Although there are still some unsolved challenges such as sensor accuracy, data reliability and the cost of the sensors itself, significant progress have been made in all of these areas. The motion control area of the control software has also matured significantly, and is already used in different degrees of application in Advance Driver Assistant Systems in conventional vehicles [5]. The focus of this paper is therefore on path planning which is yet to mature to a level that is acceptable for autonomous vehicle to be running on public roads.

## A. *History of Path Planning*

Path planning refers to the act of the robot being able to find a traversable path from one location to another. Path planning have their roots in indoor robotics and computer gaming design, where the environment is either static, less dynamic or known well in advance. These solutions however are not directly applicable to autonomous ground vehicle application as the real world scenario is highly dynamic and cannot be predicted with accuracy in advance. The earliest path planning implementations had only a single planner that planned the complete path prior to start of motion. This concept was further improved to handle more difficult scenarios by having two planners. The first one was refered to as the "global planner" planned a complete path for the vehicle through a static environment. The second planner was refered to as the "local planner" generated safe motion trajectory considering both static and dynamic obstacles while following the global path [6]. The two level planning solutions were found to be sufficient for vehicle applications less dynamic or in controlled environments and were not efficient for higly dynamic scenarios. For driving in complex real world scenarios a three level architecture became increasingly popular [1]. In the three level architecture the third planner sandwiched between the global and local planners was referred to as a behavior planner. Operating at a slower refresh rate than the local planner and tasked with planning complex behaviours of the vehicle, the behaviour lowers the workload of the local path planner by reducing the number of trajectories to evaluate [7].

## B. *Objectives of path planning and challenges.*

The quality of the generated path plan and its acceptability differs based on the application. To review the capability of the present state of the art path planning solutions the following list of objectives were identified as the necessary requirements of successful autonomous ground vehicle path planning,

a. Feasible: Path feasibility refers to a path that does not pass through obstacles or non-traversable areas.
b. Safe: "Safe path" refers to the one that is at acceptable distance away from obstacles,
c. Optimal: "Optimal path" refers to the one with either "shortest distance", "least travel time" or "least fuel energy used",
d. Usable Path: In dynamic environments a path can become unusable over time. Therefore the path generation process has to be fast enough so that it is usable in real-time,
e. Adaptive: In dynamic environments changes are inevitable, the planner should be able to adapt to those changes to allow continuous uninterrupted motion,
f. Efficient and Progressive: The plan should be based on quick decision making to enable progressive movement in traffic,
g. Interactive: The planning should generate appropriate vehicle behaviours that fits with the dynamic traffic scenario. This implies the vehicle motion following those paths does not cause disturbance to the traffic flow and therefore does not add to traffic congestion problem.

There have been attempts of autonomous vehicle driving on public roads either under supervision or in controlled environment [4],[8],[9]. However we are yet to witness unaided demonstration of this technology on busy intersections such as busy un-signalised roundabouts. While autonomous vehicles are expected to behave well when rules exists, it is not expected that every intersection on future roads will have a control signal to regulate traffic. Also many of the roundabouts in Europe are made increasingly made "un-signalised", as they have shown to reduce traffic accidents, a claim backed by statistical evidence [10]. Also and recent trend suggests intersections are increasingly being replaced by roundabouts as they are considered less prone to accidents [11]. This implies that autonomous vehicle will have to identify and use priority rules while handling intersection. Also it is virtually unthinkable that the landscape will completely change and all human driven vehicle will be off-road. This implies that autonomous vehicle will have to share the roads with non- autonomous and semiautonomous traffic. Therefore being able to successfully plan its navigation within these settings makes the requirement of an effective path planning necessary requirement.

Traffic scenarios such as un-signalised roundabouts are too complex to be characterised by few set of patterns. The behaviour of other actors (road users) that have different level of tactical skill [12], [13] and manoeuvring capability (truck bus ,car motorcycle etc.) leads to multiple scenarios variations. This study will focus on the challenges to path planning such traffic scenario presents with the case study involving an un-signalised roundabout as shown in Fig.2.

*(a)* *(b)* *(c)*

*Fig.2. Scenario illustration for vehicle turning right at a roundabout.*

This paper uses the UK driving rules as guiding principles of path planning. The priority for vehicles at junction are therefore decided according to the "UK Highway Code", This code says that the vehicle on the right has priority to enter the junction and vehicles already in the junction have priority over vehicle trying to enter the junction. These rules however are not always strictly followed in real world. Also some vehicles navigate the intersections more efficiently than others depending on the driver's tactical skill and manoeuvring capability leading to inconsistent behaviours. Fig.2. highlights some scenarios to give a brief understanding on how a vehicle approaching a junction to turn right can have different possibilities depending on the dynamic scenario. In scenario "a", the blue vehicle will wait for the "red" coloured vehicle to enter the junction as it has reached the give-way line and has priority. In scenario "b", it can safely enter the junction with the knowledge that the "green" coloured vehicle has priority and will necessitate that the "red" vehicle has to stop at the give-way line. In scenario "c" again the intention of the "red" coloured vehicle turning left increases the chances of the blue vehicle entering the roundabout. The above scenario are not an exhaustive list but highlight how interpreting the scenario effectively can lead to decisive interaction based decision making. Most demonstrated techniques such as those based "open space" search methods or "trajectory propagation" methods are not efficient in these scenarios as the very existence of a vehicle already in the roundabout, and a vehicle approaching from the right would lead to the blue vehicle stopping all the time. This unnecessary wait leads to reduced intersection flow efficiency and increased traffic congestion [14]. While these demonstration covered a vast number of traffic scenarios, highly demanding and dynamic scenarios such as a busy roundabout were not covered. This highlights the gap that exists between "expert human drivers"- who have shown the ability to successfully plan and execute navigation in such scenarios and current state of the art autonomous vehicle path planning technology. This paper therefore reviews the current state of the art to highlight the limitation of the existing solutions and the technological gap then proposes a novel behaviour planner to fill this gap.

## II. REVIEW OF CURRENT S.O.A PATH PLANNERS.

### A. *Global Path Planners*

In this study global path planning refers to the process of finding a long-term path from the vehicles current location to a desired destination. The global path objectives are that the generated path needs to be feasible, safe and optimal. Global path is planned in a known and generally static world map, and has travel times lasting over minutes/hours. These paths can be planned prior to travel/offline and does not involve frequent re-planning unless more information is available that significantly affects the quality of the chosen path. Fig.3. gives a broad categorisation of the types of techniques used for global path planning.

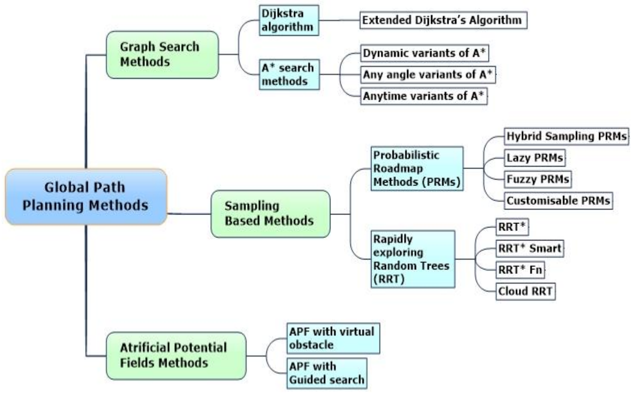


*Fig. 3. Global Path Planning Techniques.*

Most of the path planning methods shown in Fig 3 are inspired by indoor robotic and computer video gaming. These methods have been greatly researched in academia and have now been successfully used to plan global path in static environments. A brief description is given below,

a. The "graph search" methods require a prior world model before a path can be found. The accuracy of the solution depends on the available world information. Sensing and interpretation inaccuracy can lead to frequent requirement of re-planning. The Dijkstra's search methods [15],[16] and A* search methods and its variants [17],[18],[19],[20],[21],[22],[23],[24] are in this category.
b. The "sampling" based methods do not require prior environmental modelling, and have the advantage over the "graph search" methods in that they can plan a path with incomplete knowledge of the world. RRT based methods [25],[26],[27],[28],[29],[30],[31] and the PRM based methods and its variants [32], [33], [34], [35], [36], [37] are in this category.
c. The "Artificial Potential Field" methods are based on laws of physics. Build on the rules of attraction towards goal and repulsion from obstacles these methods are easy to implement. They however suffer in tight environments and generate unstable oscillatory path near obstacles. They also does cannot guarantee a solution and sometime fail to generate a successful plan. Following are some of the implementations of Artificial Potential Field and its variants [38],[39],[40].

Successful demonstrations of global path planning in static environments or environments that have been known in advance shows that the above listed methods are capable of achieving the objective of global path planning[41], [42]. Therefore this study concludes that global path planning methods are quite mature enough to meet the demands of the autonomous ground vehicle.

### B. *Local Path Planners*

The local path planners are tasked with finding a feasible, safe and optimal trajectory that connects various state points/waypoints of the global path in real time. These trajectories are planned within the sensor range of the vehicle and they consider both the static and dynamic nature of the surrounding environment. The planner objective is to generate future trajectory that are usable manoeuvrable and optimal. Fig.4. gives a broad categorisation of the different methods in local path planning.

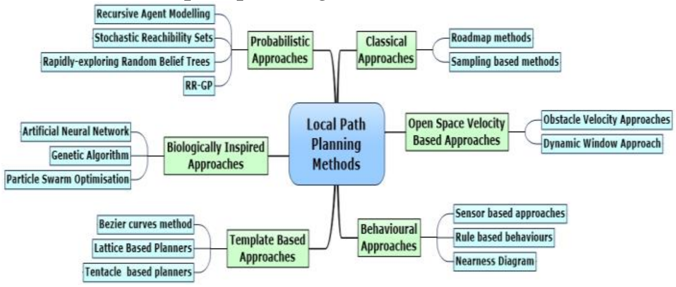


*Fig.4. Local Path Planning Techniques.*

a. The classical methods are similar to global path planners with re-planning to cater for dynamic environments. Classical methods include, graph based planners [43],[44],[45],[46], and Sampling based [47],[48].
b. The open space velocity based approaches are based on finding an admissible velocity trajectory. The methods in this category include "obstacle velocity" approach [49], [50], [51], and the dynamic window approach and its variants [52], [53], [54], [55].
c. The behaviour based approaches generate a continuum of trajectories based on unique vehicle behaviour such as lane following, vehicle following etc.,[56],[57], [58].
d. Template based methods plan the trajectory using a set of prior defined trajectory templates. Methods in this category include Bezier curves approach [59], lattice based planners [60],[61],[62] and tentacles based planners [63],[64].
e. Biologically inspired methods plan the trajectory using traditional optimisation techniques. Methods in this category include, Artificial Neural Network [65], Genetic Algorithm [66],[67],[68], Particle Swarm Optimisation [69],[70], [71].
f. Probabilistic based approaches are a recent trend and incorporate the environmental uncertainty within the planned trajectory. Methods in this category include recursive agent modelling [72], stochastic reachability sets [73],[74], Rapidly Exploring Random Belief trees [75] and RR-GP [76].

The local path planning methods in autonomous vehicle discussed above have been shown to be capable enough to generate manoeuvrable trajectories in real-time when the behaviour is selected through a behaviour planner [77], [78]. This study therefore concludes that the methods described above are sufficient to meet the objectives on the local planner.

### *C. Behaviour Planners*

The behaviour planner objectives as part of the path planning solution are to generate fast, adaptive and interactive behaviours for the local planner to generate local trajectories. The Darpa Urban Challenge (DUC) saw for the first time behaviour planners used in many of the vehicles. One of the main reasons for their extensive use was due to the need to handle urban traffic scenarios. The early implementation of the behaviour planners was mainly of three types,

1. Reactive - state machine based planners [78],
2. Layered - hierarchical state machine based planners [7]
3. Strategic - logic selection based planners [79].

These planners performed reasonably well for the scenarios they were tuned for, but were seen to be inefficient and led to many failures during the testing when the scenario was not clearly perceived. Since then attempts have been made to develop other types of behaviour planners that include those based on fuzzy logic [80], multi-objective cost function [81] and more recently those based on the Markov Decision Process [82],[83]. These planners however still suffer from the need for extensive tuning and are also not scalable to complex dynamics of real world scenarios, The MDPs based planners become computationally intractable when more actors are considered. These behavioural planners are also "less-adaptive and therefore leads to a generally defensive behaviours which is not acceptable as it leads to traffic congestion issues and poor throughput from the intersections.

After reviewing the three planners which form the part of a path planning solution it is clear that the global path planner and the local path planner are well equipped with methods that can achieve the respective objectives. However the local planner depends on the effective behaviour planning from the behaviour planner. As highlighted above although there are several different types of behaviour planners that can plan successful behaviours in less complex scenarios, when the scenario becomes more dynamic and has multiple actors these methods fall short in delivering efficient solutions. Human drivers have generally shown "expert" ability to tackle such highly dynamic and complex scenarios. Therefore to address the gap in the path planning a "human like" adaptive tactical behaviour planner is proposed in this study. Section III will describe the adaptive tactical behaviour planner framework and associated modules and in section IV we discuss the merits of the proposed behaviour planner.

## III. ADAPTIVE TACTICAL BEHAVIOUR PLANNER

The proposed novel behaviour planner framework is motivated by how experienced human drivers plan their behaviours in different traffic situations [84],[85]. The framework introduces a novel approach to mimicking human behaviour planning perception-prediction-action by having a three module behaviour planning framework. These three modules are Situation Awareness (SA), Behaviour Prediction (BhvPrd) and Behaviour Selection (BhvSel) This framework also incorporates the human tendency of discretising complex scenario into manageable phases [86]. In this proposed framework the scenario is discretised into three phases i.e. "entry phase", "intermediate phase" and the "exit phase". In the context of the roundabout scenario the three phases are approach to the roundabout, the entry and travel within the roundabout and the exit of the roundabout. The behaviours in each of these phases are then stitched together over the temporal space to give a continuum of vehicle behaviours. The proposed behaviour planner is shown in Fig 5

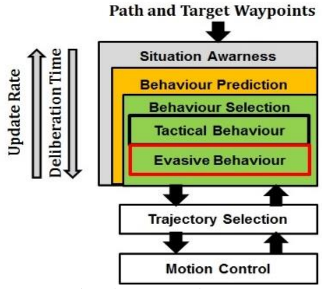


*Fig.5. Tactical Behaviour Planning Framework.*

### *A. Situation Awareness (SA)*

The SA module deals with knowing the position of the autonomous vehicle and its surroundings. A term made famous by "Endsley" [87], in this framework SA essentially involves perception of the individual parts of the scenario and projection of this abstracted world information on the scenario map. In the proposed approach this information is collated to build a dynamic attribute based "situation map" using scenario attributes seen in Fig.6.

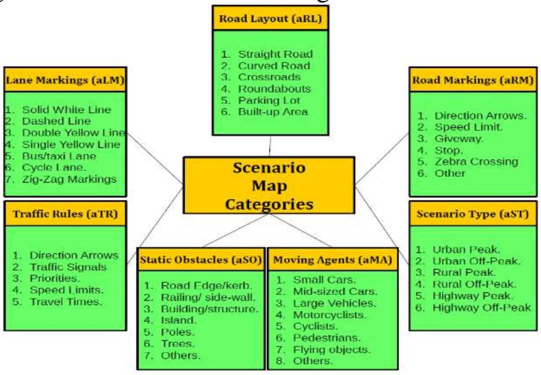


*Fig.6. Scenario Map Attributes.*

The attributes in each of the category classes shown in Fig.6, are not an exhaustive list and will be evolved with further research. The attributes relevant to the scene in question are projected on to the static scene of the road. The regular update of temporal information creates a dynamic map of the traffic scene referred in this study as a "situation map". Fig 7 gives a graphical illustration of how the map is formed. This scenario map is refreshed at fixed time stamps and results in identifying, critical actors to enables the planner to predict the evolution of the traffic scenario.

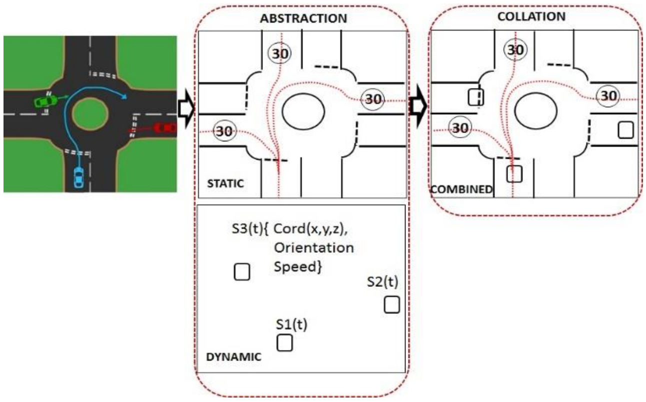


*Fig.7. Illustration of map construction for example Scenario.*

### *B. Behaviour Prediction (BhvPrd)*

The behaviour prediction module is designed with the ability to predict future behaviours of the other actors in the scene based on their current states and past movements. The behaviour of any moving actor also depends of traffic rules applicable for the scenario and their interaction with other moving actors. The designed behaviour prediction is stochastic as very rarely one can get complete information form the sensing units for complete and accurate prediction.

Behaviour prediction has been in the automotive domain for a long time, with most of the current approaches being motivated by collision/crash avoidance techniques found in Advance Drive Assisted Systems (ADAS). There are mainly two approaches that have been researched extensively. The first approach involve future trajectory prediction using the present and past physical state parameters of the actors[88]. The second approach involve trajectory matching where a matching trajectory is selected from statistically populated database of possible behaviours[88]. Both these approaches are not very efficient and are unable to predict behaviours in real time especially when the number of actors increase. In this study the behaviour prediction is interaction based, and the behaviour of other actors is predicted based on temporal evolution of behaviour through the use of Dynamic Bayesian Network (DBN). This approach is using similar concepts used by Lefèvre et al [89] however considers the Traffic rules case as a separate exclusive node. The graphical representation of the DBN framework is shown in the Fig 8

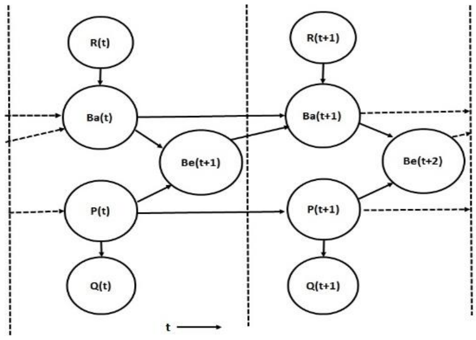


*Fig.8. Behaviour Prediction framework using DBN.*

$B_e$: is the expected behaviour of a moving actor.
$B_a$: is the actual behaviour comprising of the actors present intention" ($I$) and its present manoeuvre ($M$).
$P$ : is the estimated physical state of the actor.
$Q$: is the measured state from externally sensed parameters of Speed S and Orientation O.
$R$: is the state of specific traffic rules and encompasses the expectation according to the traffic rule.

The proposed DBN framework enables the behaviour prediction module to predict the expected behaviour of the actor in question based on its past states. Therefore the expected behaviour $B_e$ at a future time step (t+1) is given by

$$P\left(B_{e(t)} \middle| B_{a(t-1)}, P_{(t-1)}\right) = P\left(B_{e(t)} \middle| M_{(t-1)}, S_{(t-1)}, O_{(t-1)}\right)$$

The other variable of interest is the actor's intention at the scenario which depends on its previous intention and the traffic rules and the expected intention is given by

$$P\left(I_{(t)} \middle| B_{a(t-1)}, B_{e_{(t)}}\right) = P\left(I_{(t)} \middle| I_{(t-1)}, R_{(t)}, B_{e_{(t)}}\right).$$

The behaviour intention (stop/cruise/accelerate/decelerate) is than evaluated against the expected behaviour to check if the vehicle is compliant/non-compliant to follow priority rules. The behaviour manoeuvre (turn-right/turn-left/straight) are based on matching with the exemplar paths built using statistically collected data.

### C. *Behaviour Selection (BhvSel)*

This is the final module of the proposed behaviour planner framework and is tasked with having to select the best behaviour from a set of available behaviours. A complete set of vehicle behaviours are designed for the vehicle to choose from that are filtered based on scenario identification in the SA module. The behaviour set include lateral behaviours such as "turn left" "turn right" "move straight", combined with longitudinal behaviours such as "stop", "creep" "cruise" "accelerate", "decelerate" etc. The types of behaviour selection will make the vehicle either defensive (always taking the safest option) or progressive (taking calculated risks but operating within a safety margin). This behaviour selection is "tactical" i.e. with the learned knowledge of the scenario through the SA and with the predicted movements of the other actors from the "BhvPrd" the autonomous vehicle can select tactically competent behaviour based on the traffic scenario. The Behaviour selection is carried out through evaluation of the payoffs of every possible behaviours of the vehicle at each decision point, with the behaviour with the best payoff selected as part of the tactical plan. The behaviour planner therefore converts the difficult problem of navigating a complex scenario such as a roundabout into a control problem which is solved using the optimisation principle.

## IV. DISCUSSION

The proposed behaviour planner works on the principle that when in a structured settings, the moving actors behave rationally, i.e. they do not intentionally try to crash into each other. This implies that any actor will not try to occupy a position already occupied by another actor. Under these assumption the proposed behaviour planner is built to tactically select the best behaviour for the autonomous vehicle after having identified the expected behaviours of the actors that are competing for the same space. Below we discuss how the individual modules contribute towards this tactical behaviour

a. The "SA" module of the behaviour planner gives a fluid and fast representation of the traffic scenario. With this attribute based representation it eliminates the needs for complex mapping of the scenario which is both time consuming and difficult to analyse. The "SA" module helps filter down the critical areas and the critical actors of the scenario for "BhvPred".
b. The "BhvPred" module is designed using a temporal Dynamic Bayesian Network. The behaviour prediction for any actor is initiated when it is identified as an actor of interest. The behaviour prediction captures the interactions with other actors through its manoeuvre and intention estimation. The incorporation of traffic rules although basic at this stage, makes the prediction more representative of real world traffic scenario.
c. The "BhvSel" module selects the appropriate behaviour (longitudinal and lateral) for the autonomous vehicle. The decision of the appropriate behaviour at each timestamp is based on the payoff/ consequence of selection from all the possible behaviours. This enables the vehicle to tactically select behaviours that are efficient and safe.

The behaviour planner framework also has a risk estimation, which estimates the risk of an every tactical behaviour selected by "BhvSel" to generate appropriate evasive manoeuvres. The need for the evasive manoeuvres is either due to an unexpected behaviour of other actors or when an evasive manoeuvre is required by an emergency vehicle (police/ambulance).

# V. CONCLUSION

The behaviour planning is still an emerging field of research. The present lack of successful path planning solution that can generate efficient and safe path in scenarios such as un-signalised roundabouts has held the autonomous vehicle introduction in public roads. Human drivers have been tackling these scenarios for as long as they existed and their ability to intuitively interact with the other road users has been the main reason for their success. Having identified the objective of successful path planning and having reviewed the state of the art path planning methods there has been an acceptance that global path planning and local path planning challenges are effectively solved. However in order to be able to successfully navigate all types of real world scenarios and enable progressive uninterrupted motion, the behaviour planner is required to be more adaptive, scalable and efficient and interaction based. In this paper a novel behaviour planner framework is proposed, which is designed to promote a progressive form of driving. This proposed behaviour planner framework is expected to be tuned with statistical data in the coming months before being tested for real-world case of un-signalised roundabouts.

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