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Driving-Decision Making of Autonomous Vehicle according to Queensland Overtaking Traffic Rules

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Abstract. Making a driving decision according to traffic rules is a challenging task for improving the safety of Autonomous Vehicles (AVs). Traffic rules often contain open texture expressions and exceptions, which makes it hard for AVs to follow them. This paper introduces a Defeasible Deontic Logic (DDL) based driving decision-making methodology for AVs. We use DDL to formalize traffic rules and facilitate automated reasoning. DDL is used to effectively handle rule exceptions and resolve open texture expressions in rules. Furthermore, we supplement the information provided by the traffic rules by an ontology for AV driving behaviour and environment information. This methodology performs automated reasoning on formalized traffic rules and ontology-based AV driving information to make the driving decision by following the traffic rule. The overtaking traffic rule is our case study to illustrate the usefulness of our methodology. The case study evaluation showed the effectiveness of this proposed driving decision-making methodology.

Keywords: Autonomous Vehicle, Driving-Decision, Overtaking, Defeasible Deontic Logic.

1 Introduction

Over the last few decades, intelligent systems have been a widely accepted technology with various degrees of interaction. However, despite the constructive and promising impact, this advancement of technology has some negative impacts. For example, while we know that the technological advancement of vehicles is necessary and advantageous for society, it is also known that road crashes are one of the major concerns of global public health due to the growth of road fatalities and human disabilities. Every day, more than 3,700[1] people die due to road crashes, and it was found that the driver's behaviour is solely responsible for 90% of these crashes. From January 2011 to January

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[1] https://www.who.int/violence_injury_prevention/road_traffic/en/

2020, in Australia, 12274[2] people died in road crashes. From 2013-2017[3], in Queensland, the average number of deaths due to high speed was 58 per year. Therefore, it can be assumed that if drivers drive according to traffic rules, there might be less chance of fatalities and injuries.

An Autonomous Vehicle (AV) can be introduced to automatically make the driving decision according to road rules [1]. As AVs are designed and programmed to follow traffic rules [2, 3], therefore, it is suggested that AVs would be the immediate solution to traffic violations [4].

However, making driving decisions according to traffic rules is a challenging problem for AVs. It remains unclear how AVs will fit into the existing regulatory framework. There is no separate and comprehensive regulatory framework for AVs [5]. Leenes and Lucivero [2] mentioned that the current traffic rule model for the AV might be incomplete for some scenarios of the road. For example, in the current traffic rules, there are some open texture expressions (e.g. “can safely overtake”, “over- take when there is a clear view”, etc.), which are almost impossible for an AV to follow [6]. Also, it may not be possible for AVs to properly follow the rules related to exceptions [6]. Considering this issue, this paper proposes an automatic driving decision methodology by resolving the above-mentioned issues.

This paper intends to discuss the methodology for making the driving decision for AVs according to Queensland overtaking traffic rules. We choose overtaking traffic rules as it is one of the most challenging traffic rules, which has several complicated and varied conditions. The encoding is designed using DDL to successfully handle the exceptions and resolve the vague terms in rules. Our contributions to this work are:

- We have formalized the Queensland overtaking traffic rules using Defeasible Deontic Logic (DDL).
- We verified the formalization of rules for the AV; therefore, we formulated the AV driving information into the machine-computable format given by the simulator. We create an ontology knowledge base to make the machine-computable format of AV information.
- Finally, we design a reasoning engine to make the driving decision according to traffic rules. This reasoning engine requires the machine-computable format of AV driving information (ontology) and traffic rules (formalized).

2 Related Work

Traffic rules are generally expressed in natural language and are created for human drivers. Several research works have been done to address the challenges of traffic rule formalization for different purposes. Some significant research work about traffic rules formalization and driving decision-making of AV are given below.

The Isabelle logic theorem is proposed in [6] to formalize traffic rules to monitor the AV. Through monitoring, this research aims to ensure that AV obeys traffic rules. To do that, traffic rules are codified into Linear Temporal Logic (LTL) using High Order Logic (HOL). A verified checker is used to check the compliance of the AV

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[2] https://www.bitre.gov.au/statistics/safety

[3] https://streetsmarts.initiatives.qld.gov.au/speeding/factsheet

behaviour with encoded traffic rules. To analyze the data, the recorded information is modelled as discrete-time runs.

An expert system is presented in [7] to formalize traffic rules for controlling the autonomous vehicle in certain situations. This expert system consists of data processing algorithms, multidimensional databases, and a cognitive model of traffic objects and their relationship. To formalize traffic rules, data are grouped into two sets. One set consists of traffic lights, road markings, road signs, road types, etc. Another dataset consists of around 800 traffic rules. However, in this system, if somehow the traffic sign does not work properly (such as a green light is not working), then the AV might stop driving in the intersection and remain there for eternity.

A system, Mivar is introduced in [8] that can monitor vehicle activities in real-time and can also inform the driver about the violations of traffic rules. Mivar system consists of three main modules: a trajectory control system (lane position, a safe distance from other vehicles, etc.), a simplified technical vision system (road situation in real-time), and a decision support system (DSS). This system processes the information (road situation) in real-time that are received from the other assisted devices. Based on this information, it builds the algorithms to monitor the driver's action regarding traffic rules.

A framework for traffic scenario modelling and decision-making for automated vehicles in uncontrolled intersections is introduced in [9]. This framework builds on traffic situation ontology (i.e., lane 1, lane 2, lane 3, lane 4) and traffic rules. The traffic situation ontology is designed using semantic representation. This semantic representation of the traffic situation helps the AV by providing improved situational awareness. The decision-making rules are derived from the traffic situation ontology and traffic rules.

An ontology-based knowledge base is created to assist the vehicle in understanding the driving environment to make the appropriate decision during driving [10]. In this work, machine-understandable ontologies are used to illustrate the map (road network, road type, road condition, traffic signal, etc.) and driving situations (lane number, place, etc.). Three ontologies are created to make this knowledge base: map ontology, control ontology, and car ontology. From the experiment, it is seen that the vehicle can make the right decision for right-of-way traffic rules using ontologies and thus could avoid the collision.

The literature review shows that most of the research mainly does the encoding of traffic rules for monitoring AV and accountability checking of AV regarding traffic rules. A few studies work on driving decision-making for the AV according to traffic rules [7, 10]. Traffic rules are formalized using SWRL to make the appropriate driving decision in different environments [10]. Traffic rules are formalized to control the AV in certain situations [7]. However, none of this work solved traffic rule issues such as vagueness and rule exceptions, which are important variant features of traffic rules and can create challenges when making a driving decision. In comparison to these works, we have proposed a DDL-based traffic rules encoding mechanism that can make driving decisions for AVs by effectively handling the exceptions and resolving the rule vagueness.

3 Driving Decision Methodology

The proposed methodology consists of three modules. In the first module, traffic rules are formalized into the machine-computable format. In the second module, AV information is formulated into machine computable format to comply with the formatted traffic rules. Finally, in module three, the mapping and reasoning between traffic rules and AV information are conducted to make the driving decision. A brief description of each module is given below.

3.1 Traffic Rules Formalization

This section discusses the methodology we use to formalize traffic rules into a machine-computable format. We use Defeasible Deontic Logic (DDL) as a formal foundation of this encoding methodology. The proposed methodology works in four steps, as shown in Figure 1: define atoms, identify norms, generate if-then structure, and rules encoding.

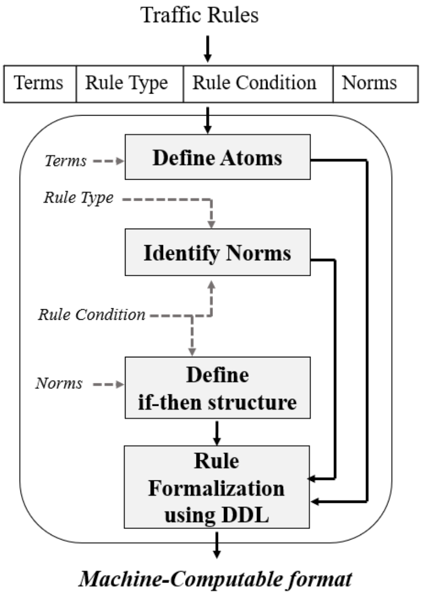

Figure 1. Workflow for traffic rules encoding.

Define Atoms: We define atoms based on terms of rules. Atom is a combination of terms and composed as a statement that only can justify as true or false. A term is a variable or an individual constant in the sentence. This work deals with those variables and constants that refer to subject (s), predicate (p), property (pr), object (o), and qualifier (q) in the rule sentence. In traffic rules, the rule structure is not equally structured. Due to this heterogeneity of the rules information, the atom structure varies. Throughout the empirical study of the Queensland Traffic Rules, we semantically define atoms in terms of five aspects which are: Subject-Predicate-Object; Subject-

Predicate-Qualifier- Object; Subject-Property, Subject-Predicate-Object-Object; Subject-Qualifier-Predicate-Object. For example, Queensland Traffic Rule, part 11 division 3 rule 140: b states that "the driver can safely overtake the vehicle". By using the proposed method of defining atoms, we can represent this rule as Predicate (subject, qualifier, object): O(d,s,v): Overtake (driver, safely, vehicle). As a result, the atom can be represented as Subject- Qualifier-Predicate -Object:

`Atom` driver_can Safely_Overtake_vehicle .

Identify Norms: In rules, norms are conditions that perform the specific action. It is used to define conditional terms and concepts of rules. Every norm is represented by one or more rules, which could be either constitutive or prescriptive rules. The constitutive rules define the terms specific to legal documents. The prescriptive rules prescribe the "mode" of the behaviour using deontic modalities: obligation, permission and prohibition. An obligation is an action or course that the subject has to perform, whereas prohibition is an action or course that the subject should not perform. Permission is the state of the action that the subject has no prohibition or obligation for the action. In this work, we identify norms based on constitutive and prescriptive rules. For example, in Queensland Traffic Rule, part 11 division 3, rule 141 states that "a driver must not overtake a vehicle to the left of the vehicle". Here we can identify norms "must not" (prohibition) of this statement.

Define if-then structure: Traffic rules specify the action of the subject. It consists of norms and conditions which control the behaviour of the subject. A rule comprises if (antecedent or premise) and then (consequent or conclusion). Therefore, a rule can be represented as:

if (*antecedent*)
then (*consequent*)

A rule may have multiple antecedents joined by logical operators which are OR, AND, XOR, and NOR. For example, in Queensland, overtaking rules, "Rule 144A: Keeping a safe lateral distance when passing bicycle rider". The rule expresses an obligation norm for the driver while passing a bicycle rider. Then by defining the atom and identifying norms, the if-then structure of this rule can be defined as:

If

rider_Passing_bicycle // *atom*

then [OBL] // *norms*

rider_KeepingASafeLateralDistance_bicycle // *atom*

Rule formalization using DDL: To model traffic rules using DDL, we consider the traffic system as a normative system, which has a set of clauses (norms) where the causes/norms are represented as if...then rules. Every clause/norm is represented by one (or more) rule(s) with the following form:

$X_1, \ldots, X_n \rightarrow Y$

Where $X_1, \ldots, X_n$ and the conditions of applicability of the norm and Y is the "effect" of the norm. According to the type of effect, we can classify the norms/rules as

- Constitutive (also known as count-as) rules that define the terms used in the normative systems, or in other terms, they create “institutional facts” from brute facts and other brute facts.
- Prescriptive rules determine what “normative” effects are in force based on the conditions of applicability.

The normative effects are modelled by the following deontic modalities: Obligation (O), Prohibition (F), and Permission (P).

We take the standard deontic logic relationships between the deontic modalities. These are exemplified below (Taking the concept of overtake, atom:overtake).

$$[F]\text{overtake} \equiv [O]\neg\text{overtake}$$

$$[O]\text{overtake} \equiv [F]\neg\text{overtake}$$

$$[P]\text{overtake} \equiv \neg[O]\neg\text{overtake}$$

Now, a complete example of encoding traffic rules using DDL is given below. For this example, we use the Queensland Overtaking Traffic Rules 141.

Traffic Rule 141

No overtaking etc. to the left of a vehicle

1. A driver (except the rider of a bicycle) must not overtake a vehicle to the left of the vehicle unless—
   (a) the driver is driving on a multi-lane road and the vehicle can be safely overtaken in a marked lane to the left of the vehicle; or
   (b) the vehicle is turning right, or making a U-turn from the centre of the road, and is giving a right change of direction signal and it is safe to overtake to the left of the vehicle; or
   (c) the vehicle is stationary and can be safely overtaken to the left of the vehicle; or
   (d) the driver is lane filtering in compliance with section 151A or edge filtering in compliance with section 151B.

Formalization of Trafic Rule 141.

Figure 3 shows the encoding (machine-computable) of Traffic rule 141. We identify and combine atoms, norms, and if-then structures using the above-mentioned mechanisms and then apply DDL on them to create the machine-computable format of the rule (e.g. r141_bicycle, r141_a, etc.). At the bottom of figure 2, the priority between the encoded rules is shown. The regulations have been ordered according to the priority of traffic rules.

```
Atom driver_OvertakeToTheLeftOf_vehicle "Overtake Left"
Atom driver_Of_bicyle "Bicycle Rider"
Atom driver_IsDrivingOn_MultiLaneRoad "Driver driving in Multi-Lane"
Atom vehicle_CanBeSafelyOvertakenIn_markedLane "the vehicle can be safely overtaken in a marked lane"
Atom markedLane_IsToTheLeftOf_vehicle "marked lane to the left of the vehicle"
Atom vehicle_IsTurningRight "the vehicle is turning right"
Atom vehicle_IsGivingRightChangeOfDirectionSignal "the vehicle is giving a right change of direction signal"
Atom IsSafeToOvertakeToTheLeftOf_vehicle "it is safe to overtake to the left of the vehicle"
Atom vehicle_IsMakingUturn "making a U-turn"
Atom vehicle_IsOn_centreOfRoad "from the centre of the road"
Atom vehicle_IsStationary "the vehicle is stationary"
Atom driver_IsLawfullyLaneFiltering "the driver is lane filtering in compliance with section 151A"
Atom driver_IsLawfullyEdgeFiltering "the driver is edge filtering in compliance with section 151B"

r141: => [F] driver_OvertakeToTheLeftOf_vehicle
r141_bicycle: driver_Of_bicyle => [P] driver_OvertakeToTheLeftOf_vehicle
r141_a:driver_IsDrivingOn_MultiLaneRoad & vehicle_CanBeSafelyOvertakenIn_markedLane
        & markedLane_IsToTheLeftOf_vehicle => [P] driver_OvertakeToTheLeftOf_vehicle
r141_b_1: vehicle_IsTurningRight & vehicle_IsGivingRightChangeOfDirectionSignal
        & IsSafeToOvertakeToTheLeftOf_vehicle => [P] driver_OvertakeToTheLeftOf_vehicle
r141_b_2: vehicle_IsMakingUturn & vehicle_IsOn_centreOfRoad & vehicle_IsGivingRightChangeOfDirectionSignal
        & IsSafeToOvertakeToTheLeftOf_vehicle => [P] driver_OvertakeToTheLeftOf_vehicle
r141_c: vehicle_IsStationary & vehicle_CanBeSafelyOvertakenIn_markedLane
        => [P] driver_OvertakeToTheLeftOf_vehicle
r141_d_a: driver_IsLawfullyLaneFiltering => [P] driver_OvertakeToTheLeftOf_vehicle
r141_d_b: driver_IsLawfullyEdgeFiltering => [P] driver_OvertakeToTheLeftOf_vehicle

r141_bicycle >> r141
r141_a >> r141
r141_b_1 >> r141
r141_b_2 >> r141
r141_c >> r141
r141_d_a >> r141
```

Figure 2. Formalization of Queensland traffic rule 141

3.2 Ontology Knowledge Base

Ontology is a way of representing knowledge in a structured framework that consists of concepts (classes) and relationships (properties). An ontology defines concepts within a knowledge domain. It is a complete semantic network where concepts are in a hierarchy. It allows communication and information sharing between software and hardware agents by facilitating the design of rigorous and exhaustive conceptual schema. An important characteristic of ontology is that it represents knowledge in the machine-computable format as RDF (Resource Description Framework) data. RDF is designed as a conceptual statement to give a clear specification for modelling data [11]. MC knowledge (RDF) representation can bridge the gap between AV perception and knowledge processing [12, 13]. Therefore, in this work, we create ontologies (machine-computable knowledge base) of AV information. Moreover, it is also proved by [12] that an ontology can effectively represent road maps, driving behaviour of the vehicle, which is helpful for AV's knowledge processing. Here, the machine-computable knowledge base is used by the formalized traffic rules to provide the input for the reasoning engine about what are the legal requirements for the AV in the particular situation identified by the data available to the AV.

The knowledge base consists of two ontologies: AV behaviour and AV environment ontology. AV behaviour ontology is created by using the behaviour information (i.e. speed, direction, lane number, etc.) of the AV. The environment ontology is created by using road information (i.e. road marking, road type, etc.) and information about AV surroundings (i.e. other vehicles, etc.). We collect all this information from the

CARRS-Q advanced simulator[4]. Moreover, based on the requirements, these ontologies can be reused and easily extended by adding another concept. To design the road map in the simulator, we collect road information (Queensland, Australia) from QLD Transport & Main Roads websites[5].

3.3 Reasoning

This section will introduce the reasoning engine to make the driving decision for AVs according to traffic rules. Figure 3 shows the working flow diagram of the reasoning process. The input of this reasoning engine is atoms (from formalized traffic rules), formalized traffic rules, and a knowledge base. The cloud shape is the ontology knowledge base. SPARQL Query Algorithm will be triggered to retrieve adequate information from this knowledge base. The proposed reasoning engine works in four steps. A brief description of these four steps is given below. Now with the help of a case study, we will demonstrate the whole working procedure of this reasoning engine.

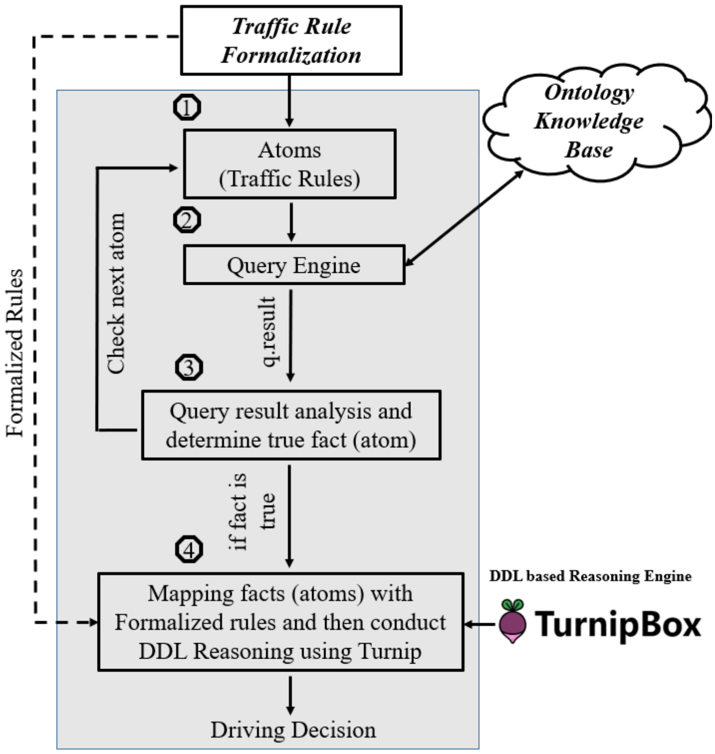

Figure 3. Reasoning Engine Workflow

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[4] https://research.qut.edu.au/carrsq/services/advanced-drivingsimulator/
[5] https://www.tmr.qld.gov.au/Travel-and-transport/Maps-and-guides

Working Procedure of Reasoning Engine (Case Study)

A simple left-overtaking case study is made in the CARRS-Q Advanced Driving Simulator. It is a 30.1-second simulation video. Figure 4 shows the overall scenario of this simulation. The simulator provides a range of data of these two vehicle's driving behaviour and the environment information in every 0.05 seconds. For this case study, we consider every 0.05 seconds as the time slot. We randomly pick a time slot (t_362: 18.05s) to describe the reasoning mechanism of the proposed driving decision-making methodology. This reasoning mechanism aims to make the driving decision at that particular time according to the Queensland Overtaking Traffic Rule 141. Below, the overall process of reasoning for that specific time slot (t_362: 18.05s) is described step by step.

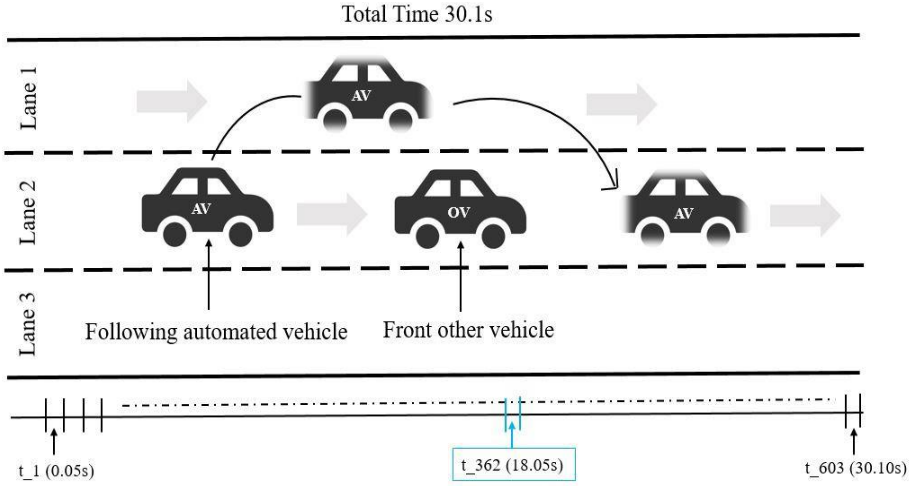

Figure 4. Left overtaking (case study)

Atom (1st Step):

Traffic Rules Formalization section provides the atoms of Overtaking Traffic Rule 141 (Division 3, Part 11) to this step. 13 atoms are generated from Overtaking Traffic Rule 141. Atoms of rule 141 are shown in Figure 2.

Query Engine (2nd Step):

The query engine contains predefined SPARQL queries for each atom and SPARQL_Query_Algorithm. These queries are made based on the empirical study of the Overtaking traffic rules of Queensland. Based on the atom, the number of queries varies. SPARQL is one of the effective query languages to access the ontology-based knowledge base. Here, we use SPARQL queries to retrieve AV behaviour and environment information from the knowledge base.

Example 1:

`Atom` driver_Of_bicyle.

Query 1-1: What type of vehicle it is? (*AV_Behaviour*)

```
prefix ab: < http :// www . semanticweb . org / bhuiyanh / ontologies /2019
/8/ untitled−ontology −50# >
SELECT  ?  Vehicle  ?  Type
WHERE   {
              ab: time_1    ab: driving ? Vehicle.
              ? Vehicle ab: is_a ? Type.
        }
Query_Result : Automated_Vehicle
```

Determining True Fact (3rd Step):

This step determines true facts (atoms) for the driving action of the AV in the above-mentioned overtaking scenario (Figure 4). In this step, for each query, we set some predefined answers. The query result is compared with those answers, and if it matches, then the system identifies that it is a true fact. For example, to verify the atom of the above-mentioned example 1, the SPARQL Query 1-1 is triggered. The answer of the query shows that it is AV & Automated_Vehicle. Therefore, it can be concluded that this atom is not true for this case study as this case study is about AV. After analyzing all atoms, the system determines all true atoms for that driving action of the AV in that particular time slot (t_362:18.05s). For this time slot, true atoms for the AV are:

`Atom` driver_Is Driving On_Multi Lane Road
`Atom` vehicle_Can Be SafelyOvertaken In_marked Lane
`Atom` marked Lane_Is To The Left Of_vehicle
`Atom` Is Safe To Overtake To The Left Of_vehicle
`Atom` vehicle_IsOn_centreOfRoad

During determining true facts, to analyze queries about safe distance and safe lane change, we briefly recall the methodology [14, 15] to identify the safe lane change, which also provides the safe distance verification of the vehicle. As soon as the automated vehicle changes the lane safely, it will maintain the safe distance according to the safe distance condition. For example,

`Atom` vehicle_Can Be SafelyOvertaken In_marked Lane — has two queries (Is AV is in safe-distance?, Can AV safely change lane?), which requires the identification of the safe distance and safe lane change of the AV.

Mapping and Reasoning in Turnip (4th Step):

Turnip is a Defeasible Deontic Logic-based reasoning tool. It is a tool that accepts facts (atoms), strict rules, defeasible rules, defeaters, superiority relations, and the modality of DL. A full illustration of Turnip is out of the scope of this research. In this research, Turnip receives the formalized rules and atoms and thus does the mapping & reasoning.

Table 1. Turnip reasoning for the case study - Permitted driving action

Rules
Formalization of Rule 141 (Figure 4)
Facts
driver_IsDriving On_Multi Lane Road vehicle_Can Be SafelyOvertaken In_marked Lane markedLane_IsToTheLeftOf_vehicle Is Safe To Overtake To The Left Of_vehicle vehicle_IsOn_centreOfRoad
Results
[P] driver_OvertakeToTheLeftOf_vehicle

In this step, true facts (atoms) and formalized rules are received by the Turnip engine for that specific time slot (t_362: 18.05s) of the above-mentioned overtaking case (Figure 4). Then, the Turnip does the mapping and reasoning on these rules and facts and makes the result as shown in Table 1. From the reasoning result, it is seen that the AV has permission ([P]) to do the left-side overtaking in that specific time slot regarding Queensland Overtaking Traffic Rule 141.

However, if any of the facts in Table 1 become false at that time slot (t_362: 18.05s) then the driving action becomes forbidden for the AV (Table 2). From this reasoning result (Table 3), it is seen that permission for overtaking is prohibited ([F]) because there is no fact (atom) about the marked lane of the left of the AV; through where the AV can overtake the other vehicle (leading vehicle).

Table 2. Turnip reasoning for the case study - forbidden driving action

Rules
Formalization of Rule 141 (Figure 4)
Facts
driver_IsDriving On_Multi Lane Road vehicle_Can Be SafelyOvertaken In_markedLane Is Safe To Overtake To The Left Of_vehicle vehicle_IsOn_centreOfRoad
Results
[F] driver_OvertakeToTheLeftOf_vehicle

4 Experiment & Evaluation

A large-scale experiment is carried out to assess the proposed driving decision methodology. Forty cases of overtaking maneuvers are evaluated based on eight realistic Queensland overtaking traffic scenarios. Every case is a specific overtaking maneuver. First, the proposed driving decision methodology assessed these overtaking maneuvers (40). Then participants (general drivers and domain experts) were asked to assess these maneuvers. After that, the proposed driving decision methodology's performance (effectiveness) was determined based on how many participants agreed with the proposed methodology's evaluation. The evaluation was conducted based on two aspects:

1) legal/illegal validation of every maneuver, and
2) reason identification if the maneuver is illegal.

Five different overtaking maneuvers are designed for each traffic scenario. Two of these maneuvers are examples of explicit legal and illegal driving actions. The other three are borderline maneuvers, which may not be directly classified as traffic violations. One of the main reasons to make these three different types of maneuvers is that traffic rules contain vague terms (e.g., safe distance, approaching vehicle, clear view, etc.) requiring judgment by the drivers. Clearly, AVs need a deterministic and algorithmic approach. The determination if atoms correspond to vague terms is delegated to the ontology and query method, where the queries implemented state-of-the-art techniques from traffic research. For example, determine whether the distance between two vehicles is safe. The parameters for the borderline situations are placed near the calculated threshold, whilst the values for the clear cases are considerably away. For instance, if a safe distance of 10 metres is determined, then values of 9 or 11 metres would be borderline, whereas 1 or 20 metres would be for clear cases.

Figure 5 shows the performance of the proposed driving decision methodology. In clear overtaking maneuver cases, on average, there is 84% legal/illegal and 86% reason identification agreement between participants and the system. In borderline overtaking maneuver cases, participant average agreement rates with the system's legal/illegal decision and reason identification are almost identical, which is 59%. The borderline cases are designed to test the human perception of the maneuvers with a very close threshold between legal and illegal in terms of a maneuver. According to the 50% outcome is truly indicative that the borderline cases are really borderline. Based on these agreement rates of clear and borderline cases, it can be stated that the proposed driving decision methodology for the AV is promising.

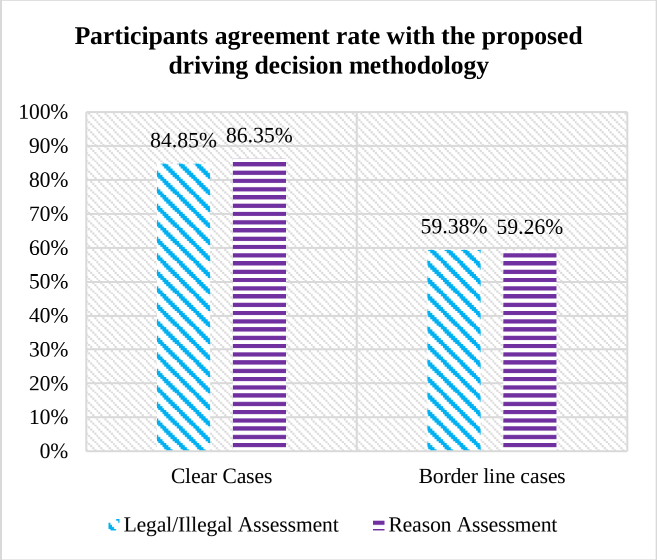

Figure 5. Performance of the proposed driving decision methodology.

5 Conclusion & Future Work

This work shows that we can formalize current traffic rules into the machine-computable format using Defeasible Deontic Logic (DDL) by effectively handling exceptions and resolving open texture expressions. This formal specification (machine-computable) of traffic rules can be processed by Automated Vehicles (AVs); thus, AVs can behave according to traffic rules.

By formally specifying traffic rules, we can make driving decisions according to the traffic rules and determine which traffic rules need additional interpretation in terms of the information available by an AV. Currently, in some existing traffic rules, there are such terms that only humans can interpret based on their perception and understanding capability without any additional information. However, an AV cannot interpret these terms without proper additional information. That's why the interpretation of some existing traffic rules is necessary to make them processable for AVs. In this work, the queries for each atom eventually represents the necessary additional interpretation for traffic rule and assists the AV in making the driving decision accurately according to traffic rules. Therefore, this formalization mechanism would be useful for the technology contributor for developing the AV and also for the transport authority to understand the adequacy of the interpretation of the particular existing traffic rules for AVs.

In future, we plan to experiment with the proposed driving decision methodology in the CARRS-Q level 4 AV in realistic test case scenarios. Furthermore, we will enhance the scope of this proposed encoding mechanism by covering other traffic environments such as lane changes, roundabouts, intersection crossings, etc.

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