Safe Driving Mechanism: Detection, Recognition and Avoidance of Road Obstacles

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Abstract: In an intelligent vehicle (autonomous or semi-autonomous), detection and recognition of road obstacle is very important for it is the failure to recognize an obstacle on time which is the primary reason for road vehicular accidents that very often leads to human fatalities. In the intelligent vehicle of the future, safe driving is a primary consideration. This is accomplished by integrating features what will assist drivers in times of needs, one of which is avoidance of obstacle. In this paper, our knowledge engineering is focused on the detection, classification and avoidance of road obstacles. Ontology and formal specifications are used to describe such mechanism. Different supervised learning algorithms are used to recognize and classify obstacles. The avoidance of obstacles is implemented using reinforcement learning. This work is a contribution to the ongoing research in safe driving, and a specific application of the use of machine learning to prevent road accidents.

1 INTRODUCTION

The statistics on global traffic accidents (World_Health_Organization 2017) are disturbing:

- Every year, about 1.24 million people die each year in road traffic accidents;
- Road traffic injury is the leading cause of death on young people, aged 15–29 years;
- Half of those dying on the world's roads are "vulnerable road users", namely the pedestrians, cyclists and motorcyclists;
- If no remedy is employed, road traffic accidents are predicted to result in the deaths of around 1.9 million people annually by 2020.

Here lies the importance of researches on intelligent transportation intended to detect, recognize and avoid road obstacles, such as ours. An intelligent transportation (Kannan et al. 2010) (Fernandez et al. 2016) denotes advanced application embodying intelligence to provide innovative services related to road obstacles, enabling various users to be better informed and makes safer, more coordinated, and smarter decisions.

Our vision of an innovative vehicle (Hina et al. 2017) is shown in Figure 1. Within this vehicle is an intelligent architecture with three main components: (1) Embedded System, (2) Intelligent System, and (3) Network and Real-time System.

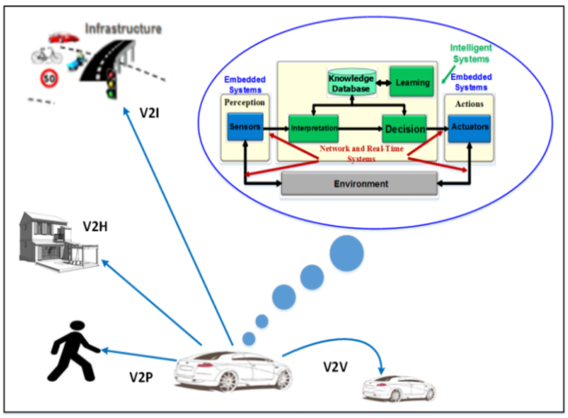

Figure 1: Smart services for an intelligent vehicle.

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The intelligent system component, for its part, has a built-in intelligence that enables the vehicle to detect, classify and avoid an obstacle. Embedded Machine learning (Ithape 2017, Saxena 2017) intelligence makes it appropriate to decide on behalf of the driver and other passengers. In this paper, we explain machine learning and types of machine learning in details. We intend to use machine learning in the detection, classification and avoidance of obstacles. To realize this, we developed a driving setting in which the driving environment is described. In such environment, we distinguished the road objects, the near objects and the obstacles. We then make use of supervise learning to identify and classify these obstacles. The work is completed by designing reinforcement learning mechanism to avoid a generic obstacle. The case is applicable to all other types of obstacles.

2 RELATED WORKS

Many researches have been made on obstacle detection, classification and avoidance as this type of system helps insuring road safety and therefore has become one of the key enablers in Advanced Driver Assistance System (ADAS). For example, the Euro New Car Assessment Program requires providing vehicles with a Front Collision Warning function (Pyo et al. 2016). Several carmakers started implementing obstacle detection and avoidance based systems such as Front Assist, Crash avoidance and Automatic Emergency Braking (AEB) in their middle and high range cars (Coelingh et al. 2010, ResearchNews 2013). Image processing techniques and computer vision models are extensively used in obstacle detection and classification researches (Bevilacqua and Vaccari 2007, Zeng et al. 2008) (Wolcott and Eustice 2016). This is justified by the use of different types of cameras such as stereo and monocular ones, which are less expensive than high-density laser scanners like LiDAR (Levi et al. 2015). Other research works, such as (Linzmeier et al. 2005, Bertozzi et al. 2008, García et al. 2013, Shinzato et al. 2014, Wang et al. 2014) use combined information obtained from several lasers and imaging sensors to detect road obstacles namely vehicles and pedestrians. The main reason being the complementarity between these different sensors and the fact that the imaging sensors do not provide enough information on the distance between the vehicle and the obstacles of the road, which is essential for obstacle avoidance systems.

In (Bazilinskyy et al. 2018), the authors proposed a system based on a deep network for road scene visualization (Figure 2). The system generates a bird's eye map showing the surrounding vehicles that are visible to the dashboard camera. To train the model, authors used a video game called GTAV to generate a massive dataset of more than one million images. Each image has two variants, one corresponding to vehicle dashboard view and the second to bird's eye view. Other information like yaw, location and distance are also collected. Authors claims the usefulness of the system to help the driver in making a better decision being more aware of the driving environment.

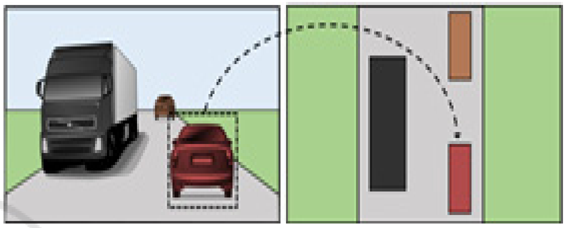


Figure 2: Input and output of Bazilinskyy, P. et al. system.

The authors in (Lan et al. 2016) worked on a real-time approach to detect and recognize road obstacles. A special focus has been made on three types of obstacles, namely abandoned objects, illegally parked vehicles and accident vehicles (Figure 3). The system follows three main consequent steps. It starts by removing the objects outside the road using a Flushed Region of Interest (FROI) algorithm. It then uses a Histogram Orientation Gradient (HOG) descriptor to detect road obstacles based on the speed of tracked objects and finally applying a Support Vector Machine (SVM) algorithm to classify the ROI and to separate abandoned objects from vehicles (both accident and illegally parked vehicles).

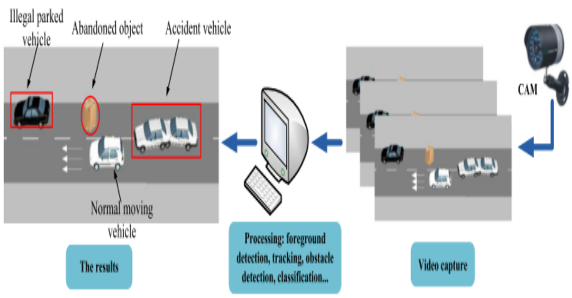


Figure 3: Overview of detection system.

The two types of vehicles are then distinguished using a special algorithm for accident vehicles identification. The authors contend that the proposed system achieved a detection rate of 96%.

Most of collision avoidance systems start by detecting and classifying the obstacle that may cause the collision before calculating the time to collision (TTC) which indicates the remaining time two consecutive vehicles are to collide. In the event of TTC, the system reacts either by alerting or warning the driver or even by acting on the vehicle causing braking (Rummelhard et al. 2016). In 2011, Volvo has commercialized its “Volvo S60” car with "Collision Warning with Auto Brake and Cyclist and Pedestrian Detection" feature to assist the driver in case of a risk of collision with a vehicle, cyclist or pedestrian (Coelingh, Eidehall et al. 2010). Other auto manufacturers such as Ford, Honda, and Nissan Mercedes-Benz have equipped their vehicles with Collision Avoidance Systems (ResearchNews 2013).

The authors of (Shinzato, Wolf et al. 2014) proposed an obstacle detection method that processes a data from a LIDAR sensor combined with single camera-generated images. The obstacles are then classified using the LIDAR point’s height information. In (Lee and Yeo 2016), the authors proposed a system for real time Collision Warning based on a Multi-Layer Perceptron Neural Network (MLPNN). The input layer was composed of five input neurons: the distance between preceding and following vehicle, speed and acceleration of the following vehicle, speed and deceleration of the preceding vehicle. The final output used a threshold discriminator of 0.5 to come out with a value of zero or one indicating whether a rear-end collision warning should be displayed.

In (Iqbal et al. 2015), the authors worked on a Dynamic Bayesian Network (DBN) method to train a model using information gathered by IMU sensor and a camera. The system was designed to provide two types of support: warning on nearby vehicles and brake alert for potential collision with the calculation of the speed and acceleration of the vehicle. The test showed a convenient performance that can be improved by adding other sensors like radar and LIDAR. Most features here have to be integrated in smart vehicle’s intelligent component.

3 THE DRIVING ENVIRONMENT

The driving environment is a set of all the elements describing the driver, the vehicle and all entities, animate or inanimate, present during the conduct of a driving activity. In this section, we will analyse the features that makes an object found within the environment an obstacle.

3.1 Environment Representation

Here, we identify the elements that are present during the conduct of a driving activity. We will describe these elements in a mathematical notion. The sets of elements present in the environment during a driving activity are: (i) the road object collection (**R**); (ii) the nearby object collection (**C**); and (iii) the obstacle object collection (**O**)

Let **R** be the set of all the road objects present in the environment **E**. Let **C** be the set of nearby road objects and **O** the set of the obstacles. Then **R** is an element of **E**, **C** is a subset of **R**, and **O** is a subset of **C**. Mathematically,

$$\mathbf{R} = \{r_1, r_2, \ldots, r_n\}, \mathbf{R} \subset \mathbf{E} \quad (1)$$

$$\mathbf{C} = \{c_1, c_2, \ldots, c_n\}, \mathbf{C} \subseteq \mathbf{R} \quad (2)$$

$$\mathbf{O} = \{o_1, o_2, \ldots, o_n\}, \mathbf{O} \subseteq \mathbf{C} \quad (3)$$

Let e be an environment object in our driving simulation platform, programmed using Unity 3D (Game_Engine 2016). Every e related to the driving environment has a tag t, a notation used for identification purposes. For all e in E, if an element e has a tag of “`RoadObject`”, then such e (denoted e_1) is a road object r_1. Mathematically, $\forall e \in E \mid \exists e_i \bullet t =$ “RoadObject” $\Rightarrow e_i = r_i \wedge R \neq \emptyset$. Figure 4 shows the specimen environment **E** and all the elements $r \in \mathbf{R}$ (all elements that are found on the road) are highlighted.

Figure 4: The specimen environment **E** and the entire road objects r’s therein ($\mathbf{R} \subset \mathbf{E}$).

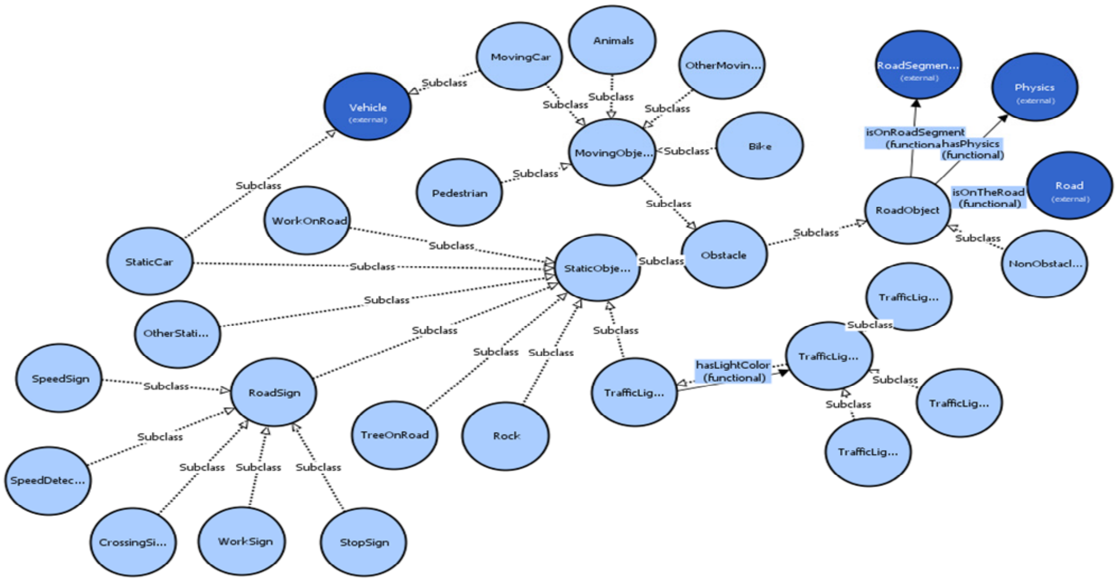


Figure 5: The ontological representation of road object collection **R**.

Figure 5 shows the ontological representation of an element $r \in$ **R**. The subclasses describe the different types of r and every subclass of Thing can have one or more individuals. The arrows "*hasSubclass*" and "*hasIndividual*" show how this is done in Protégé (Protégé 2016).

3.2 The Nearby Road Object Collection

The nearby road objects are those elements that are within the vicinity of the referenced vehicle. See Figure 6. They are parts of the road objects collection. By vicinity, we mean an element is located within the referenced radius (example: 50 meters) of a referenced vehicle. Let m be the radius of the referenced sphere (as it is the case in Unity 3D), and d as the distance between our referenced vehicle and a road object. If the distance d of the road object is less than m then such road object is considered a nearby road object c. Mathematically, $\forall r \in R \mid \exists r_i \bullet d < m \Rightarrow r_i = c_i \wedge C \neq \emptyset$.

Figure 6 shows our specimen **E** with all elements $c \in$ C highlighted. Take note that a radius from the referenced vehicle is shown. It is to be noted that this one is just one of the possible c to consider. Nearby road objects may be in front, at the back, on the left or on the right side of the referenced vehicles. Some of the nearby road objects may be obstacles while some may be not. Ontology creation is therefore important because it allows us to have a good vision of the closest road object that may be considered as road obstacles.

Figure 7 shows all elements $c \in$ C. As shown, the ontology is much smaller than the previous one, given that we only consider objects that are present in the specified radius of a sphere with our vehicle as the point of reference, with radius = m.

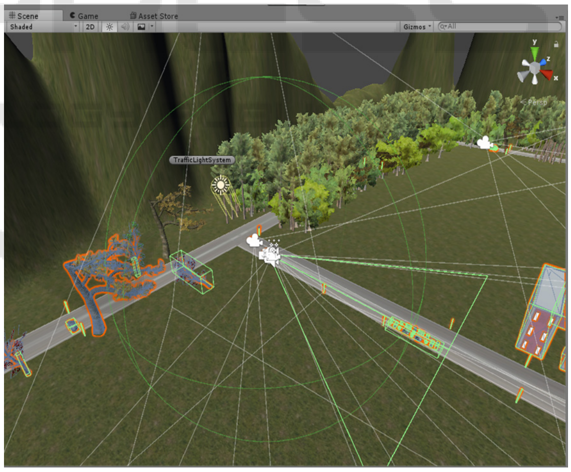


Figure 6: The nearby road objects from the referenced vehicle's perspective.

3.3 The Obstacle Object Collection

The nearby road objects are obstacles if they are in front of the vehicle (located in the same lane), the distance between it and the referenced vehicle is near, and the time to collision is near.

Let v = the current speed of our referenced vehicle, d = the distance between the vehicle and the road object r, t = the time to collision, m = radius of the

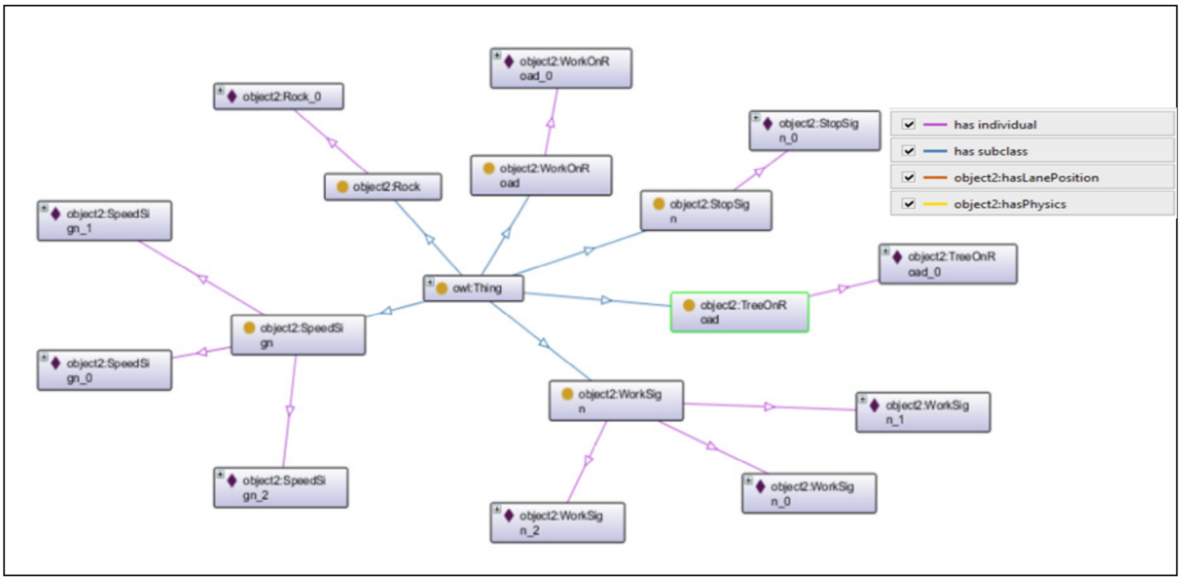


Figure 7: The ontological representation of nearby road object collection **C**.

sensor sphere, l = describes if the vehicle and the object r are on the same lane and p = the direction of the vehicle. For a nearby object $c_i \in$ C located within the vicinity of the referenced vehicle, and given that the speed of the vehicle divided by the distance between the vehicle and the nearby object is less than the time to collision, and that both the vehicle and the nearby object are on the same lane, then object c_i is an obstacle. Mathematically, $\forall c \in C \mid \exists c_i \bullet d < m \wedge v/d < t \wedge l = 1 \wedge d > 0 \Rightarrow c_i = o_i \wedge O \neq \emptyset$. Note that the parameter p is used in the computation of l.

Given that the simulation platform is in 3D coordinate system, the orientation is necessary in order to determine if vehicle s and nearby object c are on the same lane. Let dcr be the distance from the center of the road. Then:

- If p = North ∨ p = South ⇒ dcr is taken on the x plane, else ⇒ dcr is taken on the z plane.

Let dcr_s be the distance the vehicular system to the center of the road, and dcr_c be the distance of nearby object to the center of the road, then:

- $l = 1$, if $(dcr_s > 0 \wedge dcr_c > 0) \vee (dcr_s < 0 \wedge dcr_c < 0)$
- $l = -1$, if $(dcr_s > 0 \wedge dcr_c < 0) \vee (dcr_s < 0 \wedge dcr_c > 0)$

Figure 8 shows a sample road obstacle located in the same lane as the vehicle. Here, the ontology representation details are important. It is essential that all conditions for qualifying an object as an obstacle be verified.

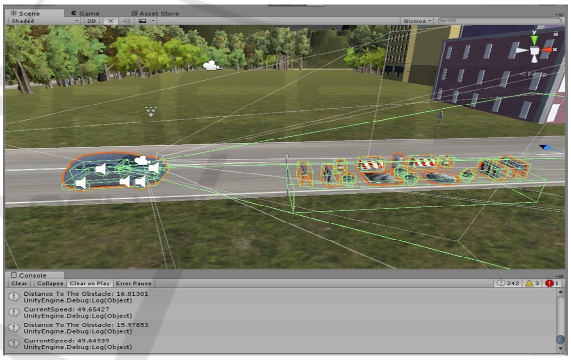


Figure 8: A sample obstacle in the simulation platform.

Figure 9 shows the properties of every obstacle $o \in$ O. Here, the ontology is presented in details for obstacle roadwork $o_1 \in$ O. The legend below shows the obstacle characteristics, such as speed or size.

In this phase, the road obstacle is already detected. The next phase should be the identification of the obstacle. An obstacle may be another vehicle (static or moving), a pedestrian, a roadwork sign, a traffic light, etc. In general, when an obstacle is detected, the referenced vehicle should stop or slow down and try to avoid such obstacle. The manner to avoid is different, depending on the type of the obstacle. For example, we avoid pedestrian differently from a rock stuck on the road. Machine learning (Mitchell 1997, Louridas and Ebert 2016) would be used to identify an obstacle.

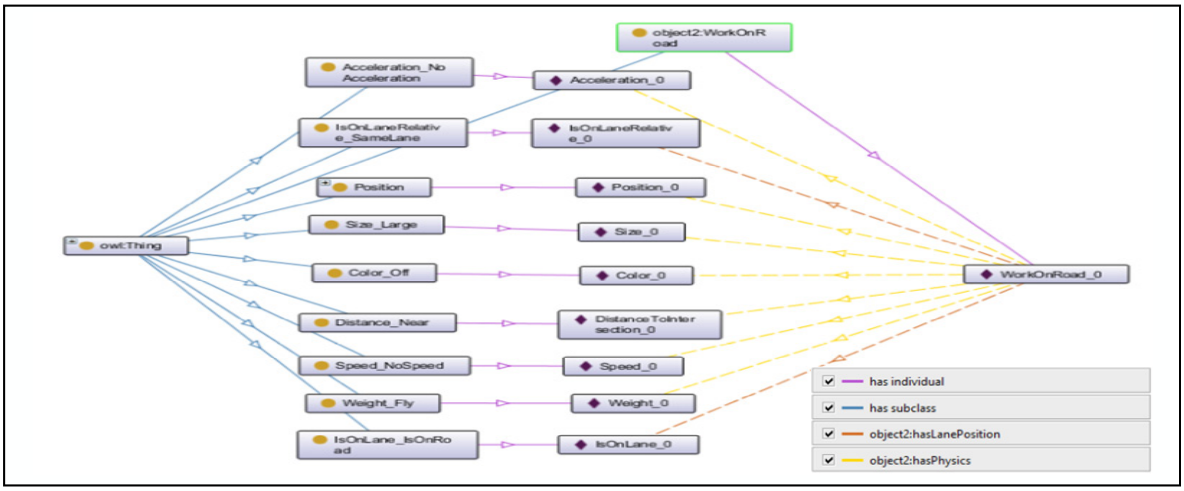


Figure 9: Ontological representation of a sample obstacle (work on the road).

4 MACHINE LEARNING FOR OBSTACLE CLASSIFICATION

4.1 Basics of Machine Learning

Supervised learning and unsupervised learning are the two main learning types in which we can divide the machine-learning world (Tchankue et al. 2013), while reinforcement learning and deep learning can be seen as special application of supervised and unsupervised learnings. Consider a normal x-y function, given a set of input x, we define y as the corresponding output value for a relation f between x and y. The differences between machine learning techniques may be explained using the basic notion of mathematics given below:

- In supervised learning, x and y are known and the goal is to learn a model that approximate f.
- In unsupervised learning, only x is given and the goal is to find f between the set of x.

Supervised learning is used for model approximation and prediction while unsupervised is used for clustering and classification (Tchankue, Wesson et al. 2013). Reinforcement learning is a particular case of supervised learning; it differs from the standard case not due to the absence of y but in the presence of delayed-reward r that allows it to determine f in order to get the right y. See Table 1.

Deep learning is a supervised or unsupervised work based on learning data representation. It uses an architecture based on multiple-layer structure for the data (Lv et al. 2015), using it for feature extraction and representation. Each successive layer uses as input the previous layer output (Bengio 2009).

Table 1: Basic mathematical representation for machine learning.

ML Method	Relation	Comments
Supervised Learning	$y = f(x)$	x and y are known and the goal is to learn a model that approximates f
Unsupervised Learning	$f(x)$	x is given and the goal is to find f for a given set of x
Reinforcement Learning	$y = f(x)$; r	r is a reward that allows determination of f in order to obtain the optimal y

(Legend: red-colored symbol means unknown data and the blue-colored symbol means known data)

4.2 Obstacle Classification using Decision Tree

Decision tree learning uses a decision tree as a predictive model. A decision tree is a flowchart-like structure in which each internal node represent a “test” on an attribute, each branch representing the outcome of the test while each leaf representing a class label for classification tree. A tree can be created by splitting the training set into subset based on an attribute value test and repeating the process until each leaf of the tree contains a single class label or we reach the desired maximum depth. There are multiple criterion that can be used to divide a node into two branch, such as the information gain, which consist of finding the split that would give the biggest

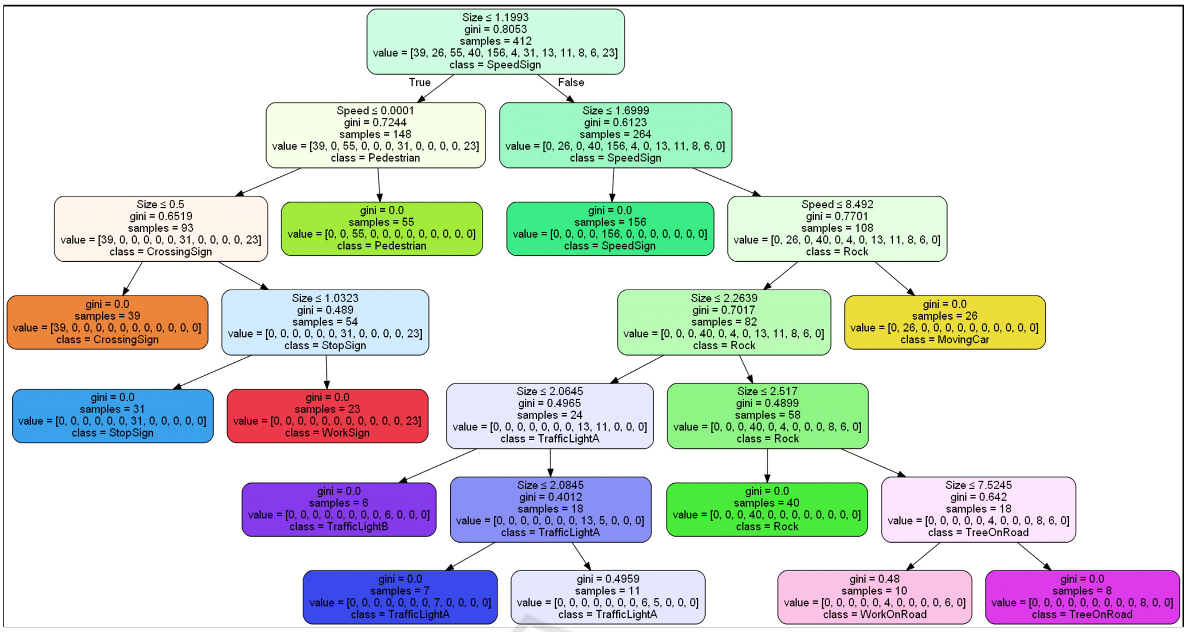


Figure 10: Obstacle classification using decision tree.

information gain, based on the entropy from the information theory (Witten, Frank et al. 2011).

Figure 10 shows the decision tree created for the object classification. Gini impurity is a measure of how often a randomly chosen element from the set would be incorrectly labeled if it were randomly labeled according to the distribution of labels in the subset. The value signifies various obstacles considered and value = [crossingSign, movingCar, pedestrain, rock, speedSign, workOnroad, stopSign, traffickLightA, traffickLightB, treeOnRoad, staticCar, workSign].

Figure 11 shows the feature importance of the decision tree. As shown, the feature that is most important for the decision-tree classification algorithm, as per simulation result, is the obstacle's size and speed; all others are not even considered.

Figure 12 shows the decision tree score in the identification of an obstacle. It uses the data as 80% for training, 20% for testing. Accordingly, it obtains 97.8% accuracy in identifying obstacles in the training set and 97.1% in identifying the obstacles within the test set. The results are satisfactory.

4.3 Obstacle Classification using K-Nearest Neighbours (KNN)

The k-nearest neighbor algorithm is a simple algorithm, which consists of selecting for an instance of data the k-nearest other instances and assigning to the first instance the most frequent label in the k instance selected. The value of k is user defined. The distance can be computed in different ways, such as the Euclidian distance for continuous variables like ours. The importance of each neighbor can be weighted; often the weight used is inversely proportional to the distance to give more importance to closer neighbor.

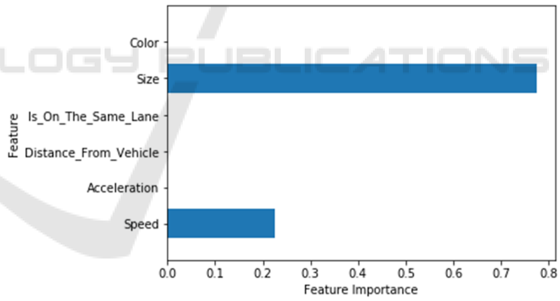
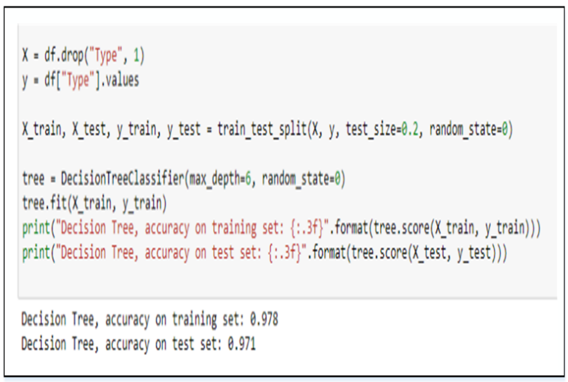


Figure 11: Obstacle classification using decision tree.



```
X = df.drop("Type", 1)
y = df["Type"].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

tree = DecisionTreeClassifier(max_depth=6, random_state=0)
tree.fit(X_train, y_train)
print("Decision Tree, accuracy on training set: {:.3f}".format(tree.score(X_train, y_train)))
print("Decision Tree, accuracy on test set: {:.3f}".format(tree.score(X_test, y_test)))

Decision Tree, accuracy on training set: 0.978
Decision Tree, accuracy on test set: 0.971
```

Figure 12: Decision tree score.

Figure 13 shows the KNN score for the data of which 80% are used for training, and 20% for testing for different values of $k = [0,\ 10], k \in \mathbb{Z}$.

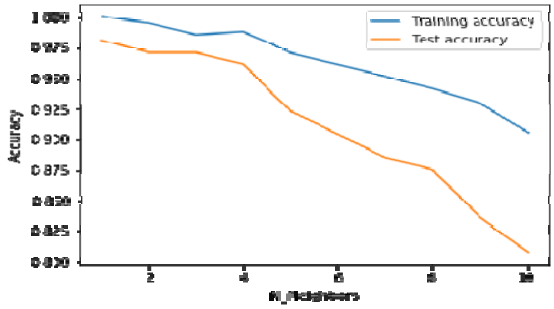


Figure 13: KNN prediction's accuracy result for training and testing with k = 0 to 10.

4.4 Obstacle Classification using Random Forest

Random Forest is a supervised learning algorithm. It creates a forest and makes it somehow random. The "forest" it builds is an ensemble of decision trees, most of the time trained with the "bagging" method. The general idea of the bagging method is that a combination of learning models increases the overall result (Donges 2018). Figure 14 shows the feature importance of the random forest.

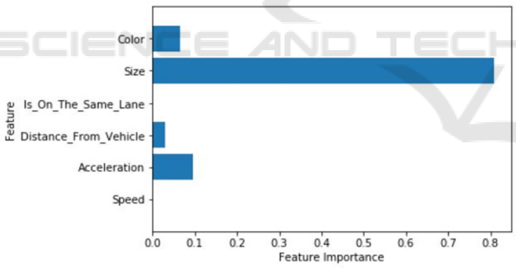
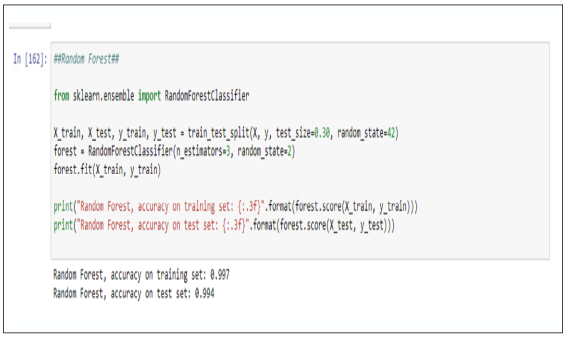


Figure 14: Features involved in KNN obstacles classification.

As shown, the feature that is most important for the random-forest classification algorithm, as per simulation result, is the obstacle's size, acceleration, color and the obstacle's distance from the referenced vehicle.

Figure 15 shows the random forest score in the identification of an obstacle. It uses 70% of the data for training, and 30% for testing. Accordingly, it obtains 99.7% accuracy in identifying obstacles in the training set and 99.4% in identifying the obstacles within the test set. The results are better than the ones obtained using decision-tree learning algorithm.



```
In [162]: ##Random Forest##

from sklearn.ensemble import RandomForestClassifier

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
forest = RandomForestClassifier(n_estimators=3, random_state=2)
forest.fit(X_train, y_train)

print("Random Forest, accuracy on training set: {:.3f}".format(forest.score(X_train, y_train)))
print("Random Forest, accuracy on test set: {:.3f}".format(forest.score(X_test, y_test)))

Random Forest, accuracy on training set: 0.997
Random Forest, accuracy on test set: 0.994
```

Figure 15: Random Forest score.

4.5 Obstacle Classification using Multilayer Perceptron

A multilayer perceptron (MLP) is a feedforward artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input and output layers. MLP uses back propagation for training the network. MLP is a deep learning method (Technopedia 2018). Figure 16 shows the feature importance of the MLP classifier.

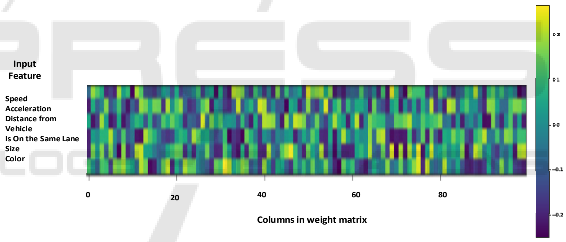
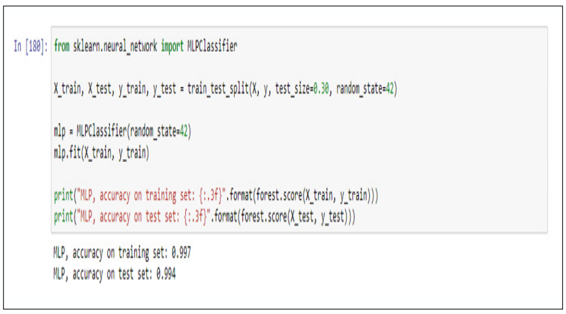


Figure 16: MLP Classifier.

Figure 17 shows the MLP score in the identification of an obstacle. It uses 70% of the data for training, and 30% for testing. Accordingly, it obtains 99.7% accuracy in identifying obstacles in the training set and 99.4% in identifying the obstacles within the test set. The results are the same as the ones from random forest learning algorithm



```
In [180]: from sklearn.neural_network import MLPClassifier

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)

mlp = MLPClassifier(random_state=42)
mlp.fit(X_train, y_train)

print("MLP, accuracy on training set: {:.3f}".format(forest.score(X_train, y_train)))
print("MLP, accuracy on test set: {:.3f}".format(forest.score(X_test, y_test)))

MLP, accuracy on training set: 0.997
MLP, accuracy on test set: 0.994
```

Figure 17: MLP Score.

6 OBSTACLE AVOIDANCE

After the obstacle detection, the system needs to avoid the obstacle. This will be done using a reinforcement learning application, building a Markov decision process (MDP) (Sutton and Barto 2017). From a mathematical point of view, reinforcement-learning problems are always formalized as Markov decision process, which provides the mathematical rules for decision making problems, both for describing them and their solutions. A MDP is composed by five elements, as shown in Table 2:

Table 2: Basic elements of Markov decision process.

Variable	Definition
State	**S** is the finite set of the possible states in an environment *T*.
Action	**A** is the possible set of action available for a state **S**.
Environment	**T(S,A,S')**; **P(S'|A,S)** where *T* represents the environment model: It is a function that produces the probability *P* of being in state *S'* taking action *A* in the state *S*.
Reward	**R(S, A, S')** is the reward given by the environment for passing from *S'* to *S* as a consequence of *A*
Policy	π(**S**; **A**) is the policy of the state (i.e. The solution of the problem) that takes as input a state *S* and gives the most appropriate action *A* to take.

The hypothesis here is the necessity to create a Markov Decision Process (MDP) based on *S*, *A*, and *r* in order to get a policy *P* able to avoid the obstacle in our environment **E**.

- Action set *A* = [Accelerate, Steer]
- Reward function *r* based on the vehicle lane and collision with obstacles
- Possible state set *S* (position of the vehicle in the environment).

The action set is composed of two actions of steering the vehicle, and accelerate (in a positive or negative way), while the reward function is based on the position of the vehicle with respect to the lane and collision with obstacles:

- Positive reward if the vehicle stays on the road and no collision occurs.
- Negative reward if the vehicle is no longer on the road and a collision is detected.

Finally, the vehicle would at every time *t* in certain state *s*, represented by the position in the environment.

6.1 The Reinforcement Learning (RL) Scene

In order to test a working avoidance system, a new scene was created. The scene, for simplicity purposes, is composed of three main actors: a vehicle, an obstacle and an intended destination. The idea is simple: the vehicle must avoid (after detecting and classifying) the obstacle. It must be able to get back to its right lane afterwards. Figure 18 shows the intended RL scene. The vehicle would be able to detect the obstacle (Figure 18(a)), avoid it (Figure 18(b)) and get into its intended destination (Figure 18(c)). With various tests and trials, we are able to achieve our goal at the end of the process.

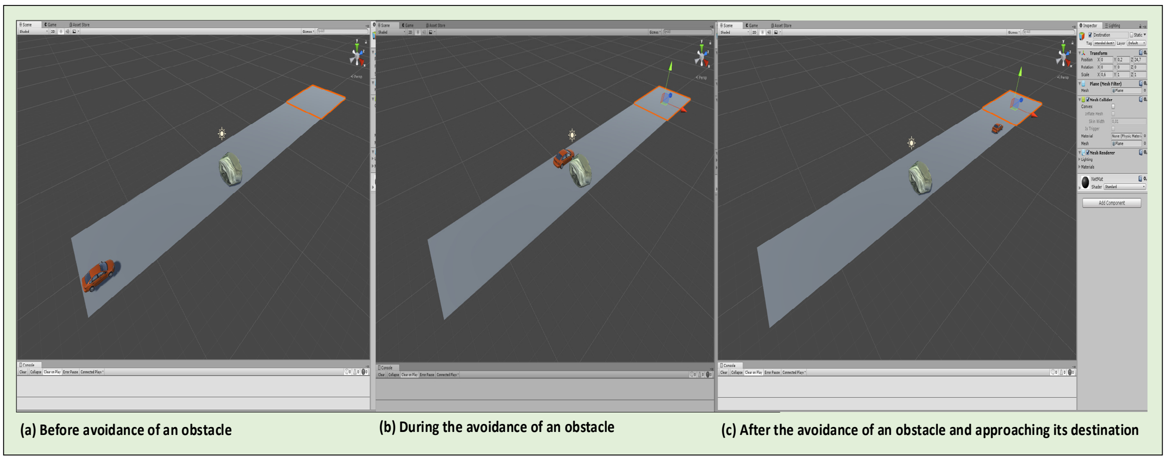


Figure 18: Reinforcement Learning for Obstacle Avoidance: before, during and after the avoidance of obstacle.

6.1.1 Reward Function

The purpose of the reward function is for the vehicle to avoid the obstacle and return to its intended destination. Equations 4 and 5 show the reward functions structure, where *collision* is a variable whose value is 1 if the vehicle reaches its target (intended destination) and 0 if collides with the obstacle, *isOnLane* is a variable whose value is 1 as long as the vehicle is on the road, otherwise its value is 0. *distanceToTarget* and *previousDistance* are variables updated every frame, representing the current and the previous distance of the vehicle and its intended destination.

$$r = \begin{cases} +1 \; if \; collision = 1 \\ +0.1 \; if \; distanceToTarget < previousDistance \\ -0.05 \; if \; distanceToTarget > previousDistance \\ -0.05 \; if \; ti < ti+1 \\ -1 \; if \; collision = 0 \; || \; isOnLane = 0 \end{cases} \quad (4)$$

$$r = \begin{cases} +1 \; if \; collision = 1 \\ +0.05 \; if \; distanceToTarget < previousDistance \\ -0.05 \; if \; distanceToTarget > previousDistance \\ -0.05 \; if \; ti < ti+1 \\ -1 \; if \; collision = 0 \; || \; isOnLane = 0 \end{cases} \quad (5)$$

A key point in the reward function is the *time penalty* factor: -0.05 for function 1 and -0.01 for function 2. This small reward is added at every frame, expressed with mathematical condition $t_i < t_{i+1}$. The *time penalty* factor is used in the RL reward function implementation, encouraging the agent to move and reach the target. The best performances were achieved with function 1, while function 2 showed high values for reward function but with worst performances.

Here, we present the three different training results. For each result, a graph shows each of the two most important statistics for the training phase. They are described below:

1. *Cumulative Reward*: This is the mean cumulative episode reward over all agents. It should increase on a successful training session.

2. *Entropy*: It describes how random the decisions of the model are. It should slowly decrease during a successful training process.

All three trainings were made using same parameters with only two changes: the *reward function* used and the *maximum step* that fixes the maximum number of steps for the training phase. The next discussion focuses on the problems and strong points in each training phase

6.1.2 Training 1: CarSimpleJ

Here, the first good performances were accomplished using the following parameters, using the 2 reward function:

```
default: trainer: ppo | batch_size: 4096
| beta: 1.0e-4 | buffer_size: 40960 |
epsilon: 0.1 | gamma: 0.99 |
hidden_units: 256 | lambd: 0.95 |
learning_rate: 1.0e-5 | max_steps: 2.5e6
| memory_size: 256 | normalize: false |
num_epoch: 3 | num_layers: 2 |
time_horizon: 64 | sequence_length: 64 |
summary_freq: 1000 | use_recurrent:
false
```

Figures 19 and 20 show the graphs for the *Cumulative Reward* and *Entropy* of CarSimpleJ. Here, the key point is that the reward is overall increasing, but has lot of peaks, both high and low. This is due to the Entropy that is not decreasing in the right way. This leads to a behaviour that sometimes gives us good results, and sometimes not, with the vehicle either reaching its destination or colliding with the obstacle.

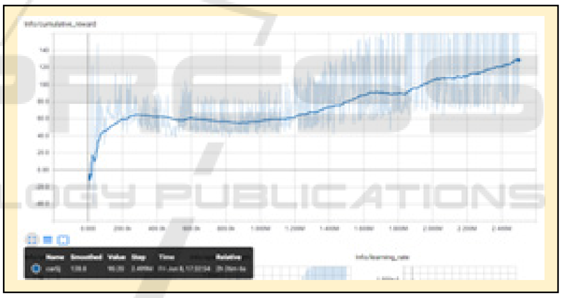


Figure 19: Cumulative reward for carSimpleJ training.

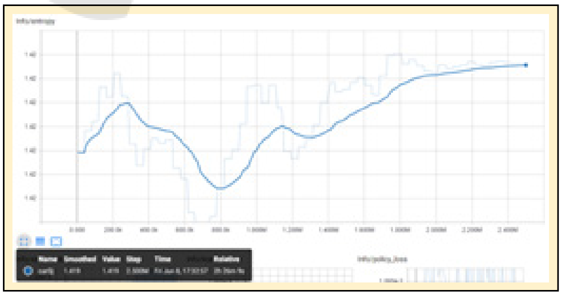


Figure 20: Entropy for carSimpleJ training.

Compared with previous simulations, this training, however, is the first one that gives us a reward that overall was increasing, hence accomplishing the task. The number of iterations, however, is small (2.5 million). The results we obtained here becomes the starting point for other simulations given that the parameters for the learning phase were suitable for the application.

6.1.3 Training 2: CarSimpleJ20

Here, we made some changes on the *maximum step* parameter, earlier fixed to 20 million, in order to see if the reward and entropy would have followed the correct behaviour. Figures 21 and 22 show the behaviour of the parameters, highlighting the correct trend, even with some low peaks for the reward.

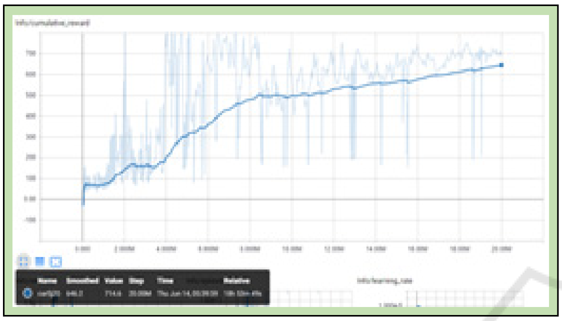


Figure 21: Cumulative reward for carSimpleJ20 training.

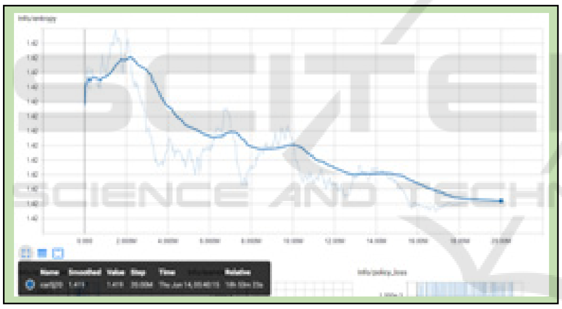


Figure 22: Entropy for carSimpleJ20 training.

From a numerical point of view, the results were very satisfying, but the problem was linked to the vehicle's behaviour. It was going too slow, taking positive reward thanks to the fact it was getting closer to the target destination. After the agent has avoided the obstacle, it was not, however, able to return on the correct lane. This overfitting behaviour was due to the reward given when the target is approaching the destination being too high relative to the value given to the final goal to achieve. Note the difference of the trend in the graph, Entropy for CarSimpleJ and CarSimpleJ20 (Figure 20 and 22).

6.1.4 Training 3: CarSimpleJ25

The behaviour obtained in the previous simulations has suggested that a change in the reward function is necessary. Indeed, Equation 1 was adopted, changing the value assigned for approaching the target and the time penalty. In Figures 23 and 24, it is possible to notice the immediate stabilization of the reward function, while the entropy is decreasing in the correct way.

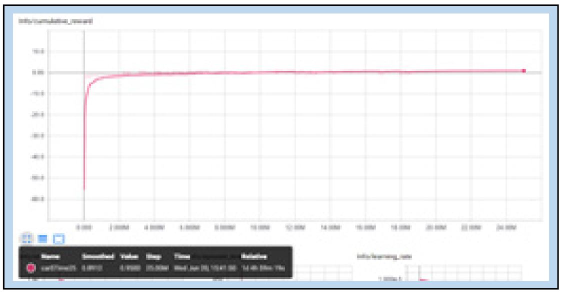


Figure 23: Cumulative reward for carSimpleJ25 training.

Figure 24: Entropy for carSimpleJ25 training.

The behaviour is almost perfect, with the agent able to avoid the obstacle and return in the correct lane, reaching the intended destination. In this simulation, the maximum step parameter was set to 25 million.

7 CONCLUSIONS

In this paper, we presented a part of our "Vehicle of the Future" project in which the vehicle's intelligent component is able to detect, identify and avoid a road obstacle. The knowledge engineering part of this paper is the systematic detection and identification of obstacles. Knowledge representation is implemented using ontology and formal specification. Machine learning techniques are used to accomplish the goal. In particular, various supervised learning algorithms (i.e. decision tree, K-nearest neighbours, random forest and multilayer perceptron) are used for identification of obstacles, and experimental results of classification are satisfactory. Intelligent avoidance of obstacle is being implemented via reinforcement learning, using Markov decision process. Future works involve the implementation of reinforcement learning in avoiding various obstacles such as moving and static vehicles, and pedestrians, among others.

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