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AN ENHANCED ECO-DRIVING STRATEGY BASED ON REINFORCEMENT LEARNING FOR CONNECTED ELECTRIC VEHICLES: COOPERATIVE VELOCITY AND LANE-CHANGING CONTROL

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ABSTRACT Purpose – This study aims to propose an enhanced eco-driving strategy based on reinforcement learning (RL) to alleviate the mileage anxiety of electric vehicles (EVs) in the connected environment. Design/methodology/approach – In this paper, an enhanced eco-driving control strategy based on an advanced RL algorithm in hybrid action space (EEDC-HRL) is proposed for connected EVs. The EEDC-HRL simultaneously controls longitudinal velocity and lateral lane-changing maneuvers to achieve more potential eco-driving. Moreover, this study redesigns an all-purpose and efficient-training reward function with the aim to achieve energy-saving on the premise of ensuring other driving performance. Findings – To illustrate the performance for the EEDC-HRL, the controlled EV was trained and tested in various traffic flow states. The experimental results demonstrate that the proposed technique can effectively improve energy efficiency, without sacrificing travel efficiency, comfort, safety and lane-changing performance in different traffic flow states. Originality/value – In light of the aforementioned discussion, the contributions of this paper are two-fold. An enhanced eco-driving strategy based an advanced RL algorithm in hybrid action space (EEDC-HRL) is proposed to jointly optimize longitudinal velocity and lateral lane-changing for connected EVs. A full-scale reward function consisting of multiple sub-rewards with a safety control constraint is redesigned to achieve eco-driving while ensuring other driving performance. Keywords Ecological driving, Electric vehicles, Reinforcement learning in hybrid action space, Velocity and lane-changing control, Reward function

INTRODUCTION

The topic of this project is building an autonomous vehicle from scratch, and more specifically, a self-driving RC car. The goal of the project is to build a model capable of autonomous driving on the track, while demonstrating the capability to perform behaviours such as lane changing. The project will go through the entire process of building such a vehicle, starting from the very RC car model and the embedded hardware platform, to the end-to-end machine learning pipeline necessary for automated data acquisition, labelling and model training. The main motivation behind the selected topic is the fast-moving progress of applied artificial intelligence (AI) and the predicted importance of autonomous vehicles on the future of humanity, from independent mobility for non-drivers and low-income individuals, reduced pollution, traffic and parking congestion to increased safety on the roads.

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Autonomous vehicles are also predicted to be relied on in some of the most complex human planned endeavours, such as space exploration. The meteoric rise of AI along with deep learning (DL) methods and frameworks, have made possible the creation of such an autonomous vehicle without expensive laboratories and years of research. Currently, there are a number of private companies as well as academic groups working on autonomous vehicles and their integration into existing regulations, laws and society itself. The advantages and quality of life improvements autonomous vehicles offer range from safer and less congested roads, reduced parking and fewer vehicles per capita to up to several thousands of dollars saved per year in travel time reduction, fuel efficiency, parking benefits and crash costs. It's obvious, with everything stated above, as well as with the well-known rise of artificial intelligence, that the field of autonomous vehicles is at its very beginnings and that it will have an important long-term impact on society, through both financial and ethical aspects. The accessibility of such technology should be made more broadly available to researches and students if the field is to continue progressing through increased discussions on important topics and not stagnate in a winter of autonomous vehicles, which is one of the reasons behind the topic of this project

LITERATURE SURVEY A. Learning a Driving Simulator, Eder Santana, George Hotz, University of Florida. Comma.ai's approach to Artificial Intelligence for self-driving car is based on an agent that learns to clone driver behaviours and plans manoeuvres by simulating future events in the road. This paper illustrates one of our research approaches for driving simulation. One where we learn to simulate. Here we investigate variational autoencoders with classical and learned cost functions using generative adversarial networks for embedding road frames. B. End to End Learning for Self-Driving Cars, Mariusz Bojarski, Davide Del Testa, NVIDIA Co-operations. They trained a convolutional neural network (CNN) to map raw pixels from a single front-facing camera directly to steering commands. This end-to-end approach proved surprisingly powerful. With minimum training data from humans the system learns to drive in traffic on local roads with or without lane markings and on highways. It also operates in areas with unclear visual guidance such as in parking lots and on unpaved roads. C. 3D Visual Perception for Self-Driving Cars using a Multi-Camera System, Christian Häne, Lionel Heng, University of Trier, Germany. Cameras are a crucial exteroceptive sensor for self-driving cars as they are low-cost and small, provide appearance information about the environment, and work in various weather conditions. They can be used for multiple purposes such as visual navigation and obstacle detection. We can use a surround multi-camera system to cover the full 360-degree field-of-view around the car. In this way, we avoid blind spots which can otherwise lead to accidents. To minimize the number of cameras needed for surround perception, we utilize fisheye cameras. Consequently, standard vision pipelines for 3D mapping, visual localization, obstacle detection, etc.

MODULES

- Data Selection and Loading
- Data Preprocessing
- Splitting Dataset into Train and Test Data

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www.ijasem.org

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- Classification
- Prediction
- Result Generation

DATA SELECTION AND LOADING

- The input data was collected from dataset repository.
- In our process, the traffic Dataset is used.

DATA PREPROCESSING

- The data can have many irrelevant and missing parts. To handle this part, data cleaning is done. It involves handling of missing data, noisy data etc.
- **Missing Data:** This situation arises when some data is missing in the data. It can be handled in various ways.
  - ✓ Ignore the tuples: This approach is suitable only when the dataset we have is quite large and multiple values are missing within a tuple.
  - ✓ Fill the Missing values: There are various ways to do this task. You can choose to fill the missing values manually, by attribute mean or the most probable value.
- **Encoding Categorical data**: That categorical data is defined as variables with a finite set of label values. That most machine learning algorithms require numerical input and output variables. That an integer and one hot encoding is used to convert categorical data to integer data.
- **Count Vectorizer:** Scikit-learn's CountVectorizer is used to convert a collection of text documents to a vector of term/token **counts**. It also enables the pre-processing of text data prior to generating the vector representation. This functionality makes it a highly flexible feature representation module for text.

SPLITTING DATASET INTO TRAIN AND TEST DATA

- Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes.
- One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.
- Separating data into training and testing sets is an important part of evaluating data mining models.
- Typically, when you separate a data set into a training set and testing set, most of the data is used for training, and a smaller portion of the data is used for testing.
- To train any machine learning model irrespective what type of dataset is being used you have to split the dataset into training data and testing data.

CLASSIFICATION

Classification is the problem of identifying to which of a set of categories, a new observation belongs to, on the basis of a training set of data containing observations and whose categories membership is known. In machine learning, classification refers to a predictive modelling problem where a class label is predicted for a given example of input data. • Classification is the task of predicting a discrete class label. Regression is the task of predicting a continuous quantity. • In machine learning, classification is a supervised learning concept which basically categorizes a set of data into classes. • Before classification, we should have split the data into test and train. • Most of data's are used for training and smaller portion of the data's are used for testing. • Training data is used for evaluate the model and testing data is used for predictive the model. • After data splitting, we have to implement the classification algorithm. • In our process, we have to use, support vector machine (SVM)

The **SVM** is one of the most powerful methods in machine learning algorithms. It can find a balance between model complexity and classification ability given limited sample information. Compared to other machine learning methods, the SVM has many advantages in that it can overcome the effects of noise and work without any prior knowledge. The SVM is a non-probabilistic binary linear classifier that predicts an input to one of two classes for each given input. It optimizes the linear analysis and classification of hyperplane formation techniques

PREDICTION

Predictive analytics algorithms try to achieve the lowest error possible by either using "boosting" or "bagging".

Accuracy − Accuracy of classifier refers to the ability of classifier. It predict the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

Speed − Refers to the computational cost in generating and using the classifier or predictor.

Robustness − It refers to the ability of classifier or predictor to make correct predictions from given noisy data.

Scalability − Scalability refers to the ability to construct the classifier or predictor efficiently; given large amount of data.

Interpretability − It refers to what extent the classifier or predictor understands.

RESULT GENERATION

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

- Accuracy

Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

$$AC=\frac{TP+TN}{TP+TN+FP+FN}$$

- Precision

Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

$$\text{Precision}=\frac{TP}{TP+FP}$$

- Recall

Recall is the number of correct

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results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

- ROC

ROC curves are frequently used to show in a graphical way the connection/trade-off between clinical sensitivity and specificity for every possible cut-off for a test or a combination of tests. In addition the area under the ROC curve gives an idea about the benefit of using the test(s) in question.

- Confusion matrix

A **confusion matrix** is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. The confusion matrix itself is relatively simple to understand, but the related terminology can be confusing

CONCLUSION

In this paper, we evaluate the performance of machine learning in recognizing traffic signs. Most importantly, we compare learning methods based on hand-crafted features with several deep learning models. The experimental results show that the property of deep learning models performs better than the traditional feature extraction method when it comes to traffic signs recognition. The obtained 99.61% accuracy rate shows that machine learning is robust and competent in recognizing traffic signs. In the future, first, we can find ways to speed up the algorithm without decreasing the accuracy. Second, we should apply these algorithms to the multi-class classification of more than 4 classes. In reality, there will exist absolutely more

FUTURE WORK

In future, it is possible to provide extensions or modifications to the proposed clustering and classification algorithms using intelligent agents to achieve further increased performance.

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