Deep Imitation Learning

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***Abstract*— In this assessment, the literature review has been conducted on deep imitation learning, and known the overview of deep imitation learning of different approaches has been noted down in different subfields of robotics. And know the various methods used in deep imitation learning for designing the deep neural networks for learning the evaluation matrices like the performance of the model, and loss of the model. The imitation learning implementation based on a path planner with a full convolution neural network is superior when it is compared with the state-of-the-art method for generating human trajectories.**

Keywords= Deep imitation learning, CNN, transfer learning, Imitation learning

I. Introduction

Deep imitation learning is the method for doing policy optimization and imitates the expert-like human demonstrated behaviors with the help of a deep neural network. Driving autonomous vehicles is more challenging in the real dynamic situation [1]. In recent years, end-to-end learning for autonomous navigation and driving has become a popular study topic in both industry and academia [2].

The two approaches of research in terms of autonomous navigation are the modular approach and the end-to-end approach. In which the modular approach contains of different modules such as localization, planning, etc., and also relies on various sensory measurements such as LiDAR and camera images taken from the robot. For accurate localization for the route planning, they need high-definition maps. Previous work was more on the modular approaches but they are failing to reach the full anatomy. The modular approach method is widely used by car manufacturers. And the end-to-end approach method mainly relies on RGB frames. An end-to-end approach method is simpler than the modular approach method and full computation is done in a single step [2].

In urban scenarios, driving the robot with dynamic objects containing dense surroundings is more challenging. The major difficulties are different road conditions including the road markings and geometry. And the second difficulty will be various traffic rules mainly speed limit and traffic lights [3].

In the robotics field, the control policies are constructed through learning from demonstration. And in the machine learning field, they are called imitation learning [5]. Deep learning-based imitation learning is considered and widely used in recent years [5].

Autonomous navigation in outdoor environments such as drones or MAVs, Despite the numerous successful applications of human-piloted and semi-autonomous drones already available, drone navigation remains an open and tough subject in robotics [6]. Imitation learning is supervised learning that is applied to reinforcement learning.

II. Literature Survey

Deep Imitation Learning in Dynamic Pedestrian Environments for Autonomous Navigation says classical methods lead to unnatural vehicle behaviors because of difficulty in modeling for pedestrian environments. In this work, they mentioned the path planning system that uses imitation learning to achieve autonomous navigation in the dynamic situations. They used a fully convolutional neural network as an approach method that maps raw sensory data to the map that helps in path extraction and they took dynamic information of the pedestrians as the input and this method is able to understand the behaviors and reacts accordingly. With this approach, they added a classification network for reducing the re-plannings from the path deviation of the global path. And implemented the imitation learning for path planning for the wheelchair and tested it in real dynamic pedestrian environments, they evaluated the performance by considering only the total running time and the total distance of the vehicle traveled used only two models they are safe path planning and mapping (SPPAM) and imitation learning-based path planner (ILPP) model. Overall, the low pedestrian environment data is collected for training and tested in different environments and yields poor performance in more challenging environments. from the result the suggested system can produce pathways for a variety of driving tasks, including the pedestrian following, the proposed method is superior for generating the human-like trajectory when it is compared with the state-of-the-art method [1].

Autonomous navigation is done using deep imitation and transfer learning, in this work the mobile platform used is the Bajaboard skateboard containing four brushless Dc motors and the board was modified with state-of-the-art hardware in order to run the DNNs. They investigate deep transfer learning techniques for learning autonomous navigation. And for extracting the features from the images they used five states of the art method they are ResNet18, ResNet50, ResNet34, Densenet121, and AlexNet. The images are taken by the front-facing camera of the mobile robot. The extracted information is having different values from the different DNN architectures. Featured extraction images are processed with a multi-layer fully connected neural network and estimated the robot angular velocity. The results obtained with different transfer learning techniques indicate the performance for estimating the accurate angular velocity using visual information. From the implemented different DNN architectures with different transfer learning techniques, an overall study has been made to note down the performance of each model, out of all the models used in this research work the AlexNet model outperforms well in terms of the performance consistency and estimation accuracy. The loss obtained from the AlexNet model is 0.056 when it is compared with other transfer learning models like the ResNet18 model with a 0.134 loss. Overall, The DNN models developed based on the AlexNet model outperform well when it is compared with other transfer learning techniques methods [2].

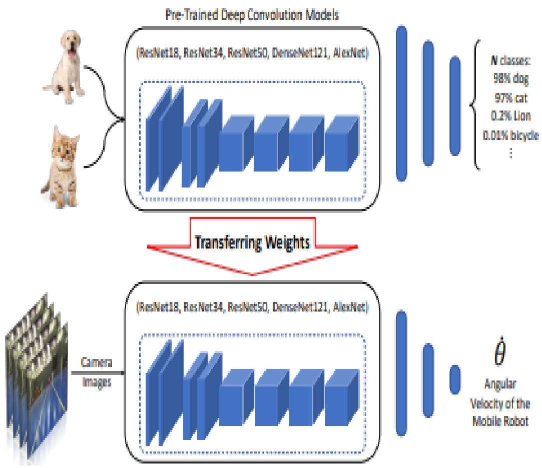

Figure1: proposed transfer learning techniques framework for learning autonomous navigation [2].

Deep imitation learning is done in general urban scenarios by enhancing the safety level for autonomous driving robots, the current methods are designed manually for driving policy is more expensive. Instead in this research work, with the help of imitation learning, they collected the data and made the computer learn and automatically improve the driving policy. And the existing methods of imitation learning are very hard to perform in urban scenarios and using deep neural network policy safety is not guaranteed. So, in this, they proposed the framework for learning the driving policy giving offline connected data for driving and safety controller is used in test time for guaranteeing the safety. The proposed method evaluates the data using a CARLA simulator, generated the bird-view input image and trained the model, and fine-tuned it. The batch size used in this case is 50. Evaluated the results in open-loop evaluation by calculating the average displacement error and noted good trajectories. And closed-loop evaluation is done from evaluation metrics by calculating the success rate. From the proposed method from the simulator, they got the ground truth information of the roads and the objects. From their experiments, their method achieved high performance in the real simulation of urban driving environments [3].

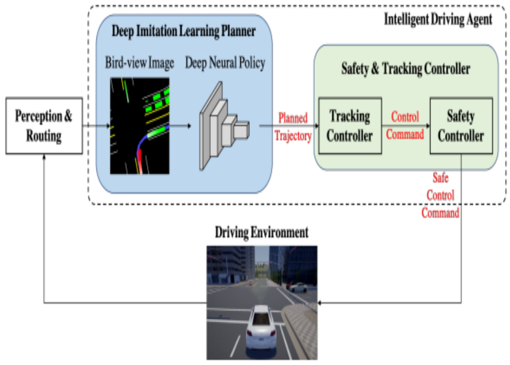

Figure 2: framework of the system where the agent takes information from the routing modules and perception. Using deep neural policy to output the planned trajectory and generate the bird-view image, safety, and tracking controller were used for calculating the safe control commands.

Deep Imitation learning for fabric smoothing by using an algorithmic supervisor, In this work, sequential pulling policies are used to flatten and because of the complexity of fabric states and dynamics, they applied deep imitation learning for learning the policies of RGB, RGBD, and depth images and taken the rectangular fabric as the sample and estimating the pick point for spreading the fabric. They have used the fabric simulator and an algorithmic supervisor for generating the data in which the algorithm accesses the complete state information. Policies are trained in the simulation using dataset aggregation and domain randomization. And presented the results for five baseline policies for learning the policies of systematic inputs as RGB, depth, and RGBD images for comparison. From the simulation point of view, they say that the learned policies achieve superior performances to the baselines. For 180 experiments done with the da Vinci Research Kit for surgical robots, the RGBD policies are trained in the simulation to attain the performance of 83% to 95%. And with an algorithmic supervisor, the effective smoothing policies are learned. And added depth sensing for coloring them alone. Baseline policies are Random, Highest (Max z), Wrinkle, Oracle, and Oracle-Expose. These are the five different baseline policies added for fabric smoothing. From the testing experiments, RGBD policies achieved higher coverage [4].

Deep Imitation Learning Pragmatic look and related imitation learning algorithm, The development of scalable imitation learning systems utilizing deep neural networks has been aided by the generative adversarial imitation learning (GAIL) algorithm. The main objective of this algorithm is to match the policy state distribution, penalizing the state allocation of the learned policy and increasing the entropy. Practically GAIL algorithm is difficult to implement because of adversarial training instability. In this paper, they implemented the GAIL algorithm and tuned the algorithms in the setup, and presented the evaluation of competing methods. And for the result, they considered non-adversarial methods. And investigated adversarial imitation learning methods on simulated robot environments as they focus more on adversarial training. And examined different deep learning-based methods and used PPO for policy updates in which it is simpler and also compares the reward functions of different algorithms. And used AIRL reward with GAIL and R1 gradient penalty for methods of adversarial. The different algorithms used in this are GAIL, AIRL, GMMIL, RED, and DRIL. They have experimented with the PyBullet version of data for deep-driven data reinforcement learning. And from the result, the GMMIL performs best when it is compared with different algorithms [5].

Deep Imitation learning uses autonomous micro aerial vehicle navigation for safe indoors, with the help of Drones or MAVs autonomous navigation is effectively done using global positioning systems. But in indoor environments using GPS for controlling the robots to automate is hard. GPS is not reliable inside indoors and is cluttered in specific environments. So, SLAM simultaneous localization and mapping are widely used. SLAM requires a high amount of computation for rendering the entire map. In this work, the policy for safe navigation for MAVs in indoor environments is learned from deep imitation learning. In order to learn the policy more effectively, the dense optical flow and monocular depth estimate are added for state representation. And CNN,3D CNN, an LSTM-RNN are three different deep convolution neural networks that are used for developing encode policy from the demonstration. And in the real environment, the performance of these policies is tested. From the results, we can see that the CNN and 3D CNN policies for MAV for the obstacle set in the test environment were successfully navigated. And policies are not navigated for LSTM-RNN neural network. And from the paper, the success rate that is tested on the test environment for CNN and 3DCNN is 90% and 0% for the LSTM-RNN. The study's findings revealed that adding dense optical flow to the monocular depth estimate improved state representation, removing issues like missing object details and possible impediments [6].

Deep Imitation learning is done using learning through drive-by imitating the best. In this paper, they trained the policy for learning imitation through autonomous driving. And used a perception system for preprocessing through input and added a controller for the output execution on the car. In the form of perturbations to the driving created the situations such as collisions. And augmented the imitation loss with additional losses for penalizing the undesirable events. ChauffeurNet model handles the complex locations in the simulation and showed whether the model is correctly responding to causal factors. And demonstrated in the real world by the model driving the car. The proposed model was trained using training data generated by randomly sampling segments of real-world expert driving and deleting portions where the car was parked for significant periods of time [7].

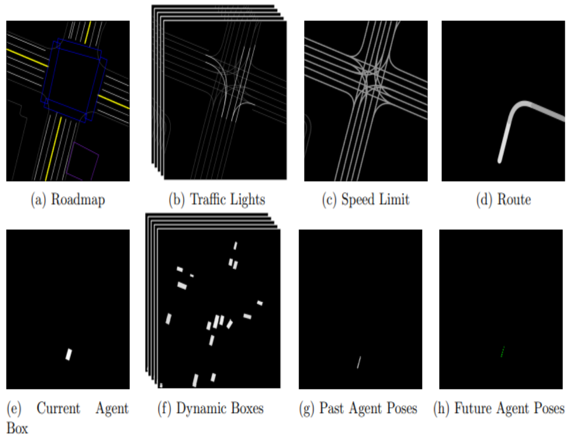

Figure 3: Model Driving inputs (a to g) and the 'h' as (output) [7].

Deep imitation learning is used for offloading the mobile edge computation, the edge-cloud computation offloading framework for the MEC networks is driven by the new deep imitation learning. The computation offloading is done for small (single mobile device) MEC systems. The main objective is to minimize the offloading cost for time-varying network environments with the help of optimal behavioral cloning. And fine-grained offloading decisions were made for the mobile device. It is a type of multi-label classification problem which contains local execution costs. For minimizing the offloading cost the decision-making engine was trained with the help of the deep imitation learning method and evaluated its performance through the study. The simulation created by them shows that their proposal performs well when it is compared with other policies. The results were evaluated on their proposal and achieved an offloading accuracy is 64.79% and reduced the offloading cost to 23.17%. optimization solution is impossible to achieve in real-time using the standard optimization methods.to address these challenges they used computation offloading decisions by leveraging the deep imitation learning [8].

Deep imitation learning and neuroevolution for optimal autonomous driving, Imitation Learning is a more efficient factor for controlling autonomous cars. Learning an end-to-end policy from the pixels is a challenging part of the imitation learning problem. With the help of deep neural networks, the pixels of high-dimensional data can be solved in real-world applications. This helps in knowing the suitable parameters for constructing the new architectures of the network. Handcrafted deep reinforcement architectures are not good for getting good performance. In this paper, they used the neuro-evolution method which is based on a genetic algorithm for getting the optimal DNN architectures in terms of hyperparameters. They modify the CNN architectures by adding more layers and filters, kernel size, etc. genetic algorithm is the technique used for solving the optimization problem. They design the deep CNN using the genetic algorithm for optimizing the parameters. The datasets are split into test and train images and evaluation metrics are calculated for the total loss of the dataset. The main goal of this is to overcome the difficulty of designing the CNNs for the specific problem. These result in the effectiveness of neuro -the evolution method for training autonomous robots [9].

III. Discussion

The training data with low-density information is collected for pedestrian navigation environment gives better human-like trajectories using a fully convolutional neural network with imitation learning of path planner approach method when it is compared with the state-of-the-art method. But it may lead the poor performance in more challenging environments. And more driving scenarios should be considered for complex environments and multiple sensors should be used for detection and yield better performance for vehicle robots in the navigation task. And also observed that using the deeper networks in the transfer learning techniques does not improve the navigation performances as the transfer learning techniques are pre-trained models consisting of their architectural weights [1].

Overall navigation is a more challenging task in the social environments for autonomous vehicles.

In terms of estimating the robot angular velocity parameter, The DNN models developed based on the AlexNet model perform better than the other transfer learning models. Further research can be taken into consideration of other transfer learning techniques to enhance their performance on robot angular velocity [2].

Taking decisions and planning the system in the urban environment is really hard for driving the autonomous robots. A safety controller is used for guaranteeing the safety of the robot for achieving good performance instead of using the deep neural network policy [3].

With end-to-end approaches, there is a key for improvement is imitation dropout, and augmenting through the exploration rates in the reinforcement learning framework will improve the performance of the model, especially for highly interactive environments [7]

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