Abstract—Automated driving in urban settings is challenging chiefly due to the indeterministic nature of the human participants of the traffic. These behaviors are difficult to model, and conventional, rule-based Automated Driving Systems (ADSs) tend to fail when they face unmodeled dynamics. On the other hand, the more recent, end-to-end Deep Reinforcement Learning (DRL) based ADSs have shown promising results. However, pure learning-based approaches lack the hard-coded safety measures of model-based methods. Here we propose a hybrid approach that integrates a model-based path planner into a vision based DRL framework to alleviate the shortcomings of both worlds. In summary, the DRL agent learns to overrule the model-based planner’s decisions if it predicts that better future rewards can be obtained while doing so, e.g., avoiding an accident. Otherwise, the DRL agent tends to follow the model-based planner as close as possible. This logic is learned, i.e., no switching model is designed here. The agent learns this by considering two penalties: the penalty of straying away from the model-based path planner and the penalty of having a collision. The latter has precedence over the former, i.e., the penalty is greater. However, it also learns to sacrifice positive rewards for following the model-based planner to avoid a potential big negative penalty for making a collision in the future. Experimental results show that the proposed method can plan its path and navigate while avoiding obstacles between randomly chosen origin-destination points in CARLA, a dynamic urban simulation environment. Our code is open-source and available online.

I. INTRODUCTION

Automated Driving Systems (ADSs) promise a decisive answer to the ever-increasing transportation demands. However, widespread deployment of ADSs is not on the horizon as state-of-the-art is not robust enough for urban driving. The infamous Uber accident [1] is an unfortunate precursor: the technology is not ready yet.

There are two common ADS design choices [2]. The first one is the more conventional, model-based, modular pipeline approach [3]–[10]. A typical pipe starts with feeding sensory inputs into a perception module. The recent breakthrough in the computer vision field caused by the advent of deep Convolutional Neural Networks (CNN) [11] enabled the development of robust perception modules. The pipe usually continues with scene understanding [12], assessment [13], planning [14] and finally ends with motor control. The biggest shortcomings of modular model-based planners can be summarized as complexity, being prone to error propagation and lack of generalization outside pre-postulated model dynamics.

The alternative end-to-end approaches [15]–[24] eliminated the complexity of conventional modular systems. With the recent developments in the machine learning field, sensory inputs now can be directly mapped to an action space. Deep Reinforcement Learning (DRL) based frameworks can learn to drive from front-facing monocular camera images directly [27]. However, the lack of hard-coded safety measures, interpretability, and direct control over path constraints limit the usefulness of these methods.

We propose a hybrid methodology to mitigate the drawbacks of both approaches. In summary, the proposed method integrates a short pipeline of localization and path planning modules into a DRL driving agent. The goal of training is to teach the DRL agent to oversee the model-based planner. The proposed method was implemented with a Deep Q Network (DQN) [25] based RL agent and the A* [26] path planner. First, the localization module outputs the ego-vehicle position, and with a given destination point, the path planner uses the A* algorithm [26] to generate a set of waypoints. The distance to the closest waypoint, along with monocular camera images and ego-vehicle dynamics, are then fed into the DQN based RL agent to select discretized steering and acceleration actions. During training, the driving agent is penalized for making collisions and being far from the closest waypoint asymmetrically, with the former term having precedence. This makes the agent prone to follow waypoints during free driving but gives it enough flexibility to stray from the path for collision avoidance using visual cues. An overview of the proposed approach is shown in Fig. 1.

Fig. 1. An overview of our framework. The proposed system is a hybrid of a model-based planner and a model-free DRL agent. Other sensor inputs can be anything the conventional pipe needs. ** We integrate model-based planners into the DRL agent by adding ‘distance to the closest waypoint’ to our state-space, where the path planner gives the closest waypoint. Any kind of path planner can be integrated into the DRL agent with the proposed method.

*E. Yurtsever, L. Capito, K. Redmill and U. Ozguner are with The Ohio State University, Ohio, US.

† These authors contributed equally to this work

Corresponding author: Ekim Yurtsever, ekimyurtsever@gmail.com

https://github.com/Ekim-Yurtsever/Hybrid-DeepRL-Automated-Driving
The major contributions of this work can be summarized as follows:

- A general framework for integrating model-based path planners into model-free DRL based driving agents
- Implementation of the proposed method with an A* planner and DQN RL agent. Our code is open-source and available online.

The remainder of the paper is organized in four sections. Section II explains the proposed methodology and is followed by experimental details in Section III. Results are discussed in Section IV and a brief conclusion is given in Section V.

II. PROPOSED METHOD

A. Problem formulation

In this study, automated driving is defined as a Markov Decision Process (MDP) with the tuple of \((S, A, P, r)\).

- **S**: A set of states. We associate observations made at time \(t\) with the state \(s_t\) as \(s_t \approx (z_t, e_t, d_t)\) where: 1) \(z_t = f_{cnn}(I_t)\) is a visual feature vector which is extracted using a deep CNN from a single image \(I_t\) captured by a front-facing monocular camera. 2) \(e_t\) is a vector of ego-vehicle states including speed, location, acceleration and yaw. 3) \(d_t\) is the distance to the closest waypoint obtained from the model-based path planner. \(d_t\) is the key observation which links model-based path planners to the MDP.
- **A**: A set of discrete driving actions illustrated in Figure 3. Actions consist of discretized steering angle and acceleration values. The agent executes actions to change states.
- **P**: The transition probability \(P_t = Pr(s_{t+1}|s_t, a_t)\). Which is the probability of reaching state \(s_{t+1}\) after executing action \(a_t\) in state \(s_t\).
- **r**: A reward function \(r(s_{t+1}, s_t, a_t)\). Which gives the instant reward of going from state \(s_t\) to \(s_{t+1}\) with \(a_t\).

The goal is to find a policy function \(\pi(s_t) = a_t\) that will select an action given a state such that it will maximize the following expectation of cumulative future rewards where \(s_{t+1}\) is taken from \(P_t\).

\[
E \left( \sum_{t=0}^{\infty} \gamma^t r(s_t, s_{t+1}, a_t) \right) \tag{1}
\]

Where \(\gamma\) is the discount factor, which is a scalar between \(0 \leq \gamma \leq 1\) that determines the relative importance of later rewards with respect to previous rewards. We fix the horizon for this expectation with a finite value in practice.

Our problem formulation is similar to a previous study \cite{21}, the critical difference being the addition of \(d_t\) to the state space and the reward function. An illustration of our formulation is shown in Figure 2.

B. Reinforcement Learning

Reinforcement learning is an umbrella term for a large number of algorithms derived for solving the Markov Decision Problems (MDP) \cite{21}.

In our framework, the objective of reinforcement learning is to train a driving agent who can execute ‘good’ actions so that the new state and possible state transitions until a finite expectation horizon will yield a high cumulative reward. The reward is quite straightforward for driving: not making collisions and reaching the destination should yield a good reward and vice versa. It must be noted that RL frameworks are not greedy unless \(\gamma = 0\). In other words, when an action is chosen, not only the immediate reward but the cumulative rewards of all the expected future state transitions are considered.

Here we employ DQN \cite{25} to solve the MDP problem described above. The main idea of DQN is to use neural networks to approximate the optimal action-value function \(Q(s, a)\). This \(Q\) function maps the state-action space to \(\mathbb{R}\). \(Q : S \times A \to \mathbb{R}\) while maximizing equation \ref{eq:1} The problem comes down to approximate or to learn this \(Q\) function. The following loss function is used for Q-learning at iteration \(i\).

\[
L_i(\theta) = \mathbb{E}_{(s,a,r)} \left[ (r + \gamma \max_{a_{t+1}} Q^\theta_{t+1}(s_{t+1}, a_{t+1}) - Q^\theta_t(s_t, a_t))^2 \right] \tag{2}
\]

Where Q-Learning updates are applied on samples \((s, a, r) \sim U(D)\). \(U(D)\) draws random samples from the data batch \(D\). \(\theta_i\) is the Q-network parameters and \(\theta_{t+1}^-\) is the target network parameters at iteration \(i\). Details of DQN can be found in \cite{25}.
C. Integrating model-based planners into model-free DRL frameworks

The main contribution of this work is the integration of model-based planners into DRL frameworks. We achieve this by modifying the state-space with the addition of $d$. Also, the reward function is changed to include a new reward term $r_w$, which rewards being close to the nearest waypoint obtained from the model-based path planner, i.e. a small $d$. Utilizing waypoints to evaluate a DRL framework were suggested in a very recent work [27], but their approach does not consider integrating the waypoint generator into the model.

The proposed reward function is as follows.

$$r = \beta_c r_c + \beta_v r_v + \beta_l r_l + \beta_w r_w$$  \hspace{1cm} (3)

Where $r_c$ is the no-collision reward, $r_v$ is the not driving very slow reward, $r_d$ is being-close to the destination reward, and $r_w$ is the proposed being-close to the nearest waypoint reward. The distance to the nearest waypoint $d$ is shown in Figure 2. The weights of these rewards, $\beta_c, \beta_v, \beta_l, \beta_w$, are parameters defining the relative importance of rewards. These parameters are determined heuristically. In the special case of $\beta_c = \beta_v = \beta_l = 0$, the integrated model should mimic the model-based planner.

Please note that any planner, from the naive A* to more complicated algorithms with complete obstacle avoidance capabilities, can be integrated into this framework as long as they provide a waypoint.

III. Experiments

As in all RL frameworks, the agent needs to interact with the environment and fail a lot to learn the desired policies. This makes training RL driving agents in real-world extremely challenging as failed attempts cannot be tolerated. As such, we focused only on simulations in this study. Real-world adaptation is outside of the scope of this work.

The proposed method was implemented in Python based on an open-source RL framework [28] and CARLA [29] was used as the simulation environment. The commonly used A* algorithm [26] was employed as the model-based path planner, and the recently proposed DQN [25] was chosen as the model-free DRL.

A. Details of the reward function

The general form of $r$ was given in the previous Section in equation 3. Here, the special case and numerical values used throughout the experiments are explained.

$$r = \begin{cases} 
 r_v + r_l + r_w, & r_c = 0 & l < \epsilon \\
 100, & r_c = 0 & l \geq \epsilon \\
 r_c, & r_c \neq 0 
\end{cases}$$  \hspace{1cm} (4)

$$r_c = \begin{cases} 
 0, & \text{no collision} \\
 -1, & \text{there is a collision} 
\end{cases}$$  \hspace{1cm} (5)

$$r_v = \frac{1}{v_0} v - 1$$  \hspace{1cm} (6)

$$r_l = 1 - \frac{l}{l_{\text{previous}}}$$  \hspace{1cm} (7)

$$r_w = 1 - \frac{d}{d_0}$$  \hspace{1cm} (8)

Where $\epsilon = 5m$, the desired speed $v_0 = 50km/h$, and $d_0 = 8m$. In summary, $r_w$ rewards keeping a distance less than $d_0$ to the closest waypoint at every time step, and $r_l$ rewards decreasing $l$ over $l_{\text{previous}}$ distance to the destination in the the previous time step. The last term of $r_l$ allows to continuously penalize/reward the vehicle for getting further/closer to the final destination.

If there is a collision, the attempt is over and the reward gets a penalty equal to $-1$. If the vehicle reaches its destination $\exists \epsilon > 0 : l < \epsilon$, a reward of 100 is sent back. Otherwise, the reward consists of the sum of the other terms. $d_0$ was selected as $8m$ because the average distance between waypoints of the A* equals to this value.
B. DQN architecture and hyperparameters

The deep neural network architecture employed in the DQN is shown in Figure 3. The CNN consisted of three identical convolutional layers with 64 filters and a $3 \times 3$ window. Each convolutional layer was followed by average pooling. After flattening, the output of the final convolutional layer, ego-vehicle speed and distance to the closest waypoint were concatenated and fed into a stack of two fully connected layers with 256 hidden units. All but the last layer had rectifier activation functions. The final layer had a linear activation function and outputed the predicted Q values, which were used to choose the optimum action by taking argmax $Q$.

C. Experimental process & training

The experimental process is shown in Figure 4. The following steps were carried repeatedly until the agent learned to drive.

1. Select two random points on the map as an origin-destination pair for each attempt
2. Use A* path planner to generate a path between origin-destination using the road topology graph of CARLA. Dynamic objects were disregarded by the A*.
3. Start feeding the stream of states, including distance to the closest waypoint, into the DRL agent. DRL agent starts to take actions at this point. If this is the first attempt, initialize the DQN with random weights.
4. End the attempt if a collision is detected, or the goal is reached.
5. Update the weights of the DQN after each attempt with the loss function given in equation 2.
6. Repeat the above steps twenty thousand times

D. Comparison and evaluation

The proposed hybrid approach was compared against a complete end-to-end DQN agent. The complete end-to-end agent took only monocular camera images and ego-vehicle speed as input. The same network architecture was employed
The evaluation of the driving performance was done with the same reward function that was used to train the DQNs.

IV. RESULTS

The proposed hybrid approach learned to drive much faster than its complete end-to-end counterpart, as can be seen in Figure 5. In this figure, the bottom dashed line indicates random policy performance. We also accepted the top dashed line as a safe driving threshold heuristically. It should be noted that the proposed approach made a quick jump at the beginning of the training. We believe the waypoints acted as a ‘guide’ and made the algorithm learn faster that way. Qualitative analysis of the driving performance can be done by watching the simulation videos on our repository.

Even though promising results were obtained, the experiments at this stage can only be considered as proof of concepts, rather than an exhaustive evaluation. The proposed method needs to consider other integration options, be compared against other state-of-the-art agents, and eventually should be deployed to the real-world and tested there.

The model-based path planner tested here is also very naive. In the experiments, only the DRL was responsible for collision avoidance. The integration of more complete model-based planners with full obstacle avoidance capabilities can yield better results.

V. CONCLUSIONS

In this study, a novel hybrid approach for integrating model-based path planners into model-free DRL frameworks was proposed. A proof-of-concept implementation and experiments in a virtual environment showed that the proposed method is capable of learning to drive safely.

The proposed integration strategy is not limited to path planning. Potentially, the same reward strategy can be applied for integrating vehicle control and trajectory planning modules into model-free DRL agents.

Finally, the current implementation was limited to output only discretized actions. Future work will focus on enabling continuous control and real-world testing.

REFERENCES

[1] P. Kohli and A. Chadha, “Enabling pedestrian safety using computer vision techniques: A case study of the 2018 uber inc. self-driving car crash,” in Future of Information and Communication Conference, Springer, 2019, pp. 261–279.

[2] E. Yurtsever, J. Lambert, A. Carballo, and K. Takeda, “A survey of autonomous driving: common practices and emerging technologies,” arXiv preprint arXiv:1906.05113, 2019.

[3] C. Urmson, J. Anhalt, D. Bagnell, C. Baker, R. Bittner, M. Clark, J. Dolan, D. Duggins, T. Galatari, C. Geyer et al., “Autonomous driving in urban environments: Boss and the urban challenge,” Journal of Field Robotics, vol. 25, no. 8, pp. 425–466, 2008.

[4] J. Levinson, J. Askeland, J. Becker, J. Dolson, D. Held, S. Kammler, J. Z. Kolter, D. Langer, O. Pink, V. Pratt et al., “Towards fully autonomous driving: Systems and algorithms,” in Intelligent Vehicles Symposium (IV), 2011 IEEE. IEEE, 2011, pp. 163–168.

[5] J. Wei, J. M. Snider, J. Kim, J. M. Dolan, R. Rajkumar, and B. Litkouhi, “Towards a viable autonomous driving research platform,” in Intelligent Vehicles Symposium (IV), 2013 IEEE. IEEE, 2013, pp. 763–770.

[6] A. Broggi, M. Buzsoni, S. Debuttisti, P. Grisleri, M. C. Laghi, P. Medici, and P. Versari, “Extensive tests of autonomous driving technologies,” IEEE Transactions on Intelligent Transportation Systems, vol. 14, no. 3, pp. 1403–1415, 2013.

[7] W. Maddern, G. Pascoe, C. Linegar, and P. Newman, “1 year, 1000 km: The oxford robotcar dataset,” The International Journal of Robotics Research, vol. 36, no. 1, pp. 1–35, 2017.

[8] N. Akai, L. Y. Morales, T. Yamaguchi, E. Takeuchi, Y. Yoshihara, H. Okuda, T. Suzuki, and Y. Ninomiya, “Autonomous driving based on accurate localization using multilayer lidar and dead reckoning,” in IEEE 20th International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2017, pp. 1–6.

[9] E. Guizzo, “How google’s self-driving car works,” IEEE Spectrum Online, vol. 18, no. 7, pp. 1132–1141, 2011.

[10] J. Ziegler, P. Bender, M. Schreiber, H. Latagah, T. Strauss, C. Stiller, T. Dang, U. Franke, N. Appenrodt, C. G. Keller et al., “Making Bertha drive – an autonomous journey on a historic route,” IEEE Intelligent Transportation Systems Magazine, vol. 6, no. 2, pp. 8–20, 2014.

[11] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.

[12] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, “The cityscapes dataset for semantic urban scene understanding,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 3213–3223.

[13] E. Yurtsever, Y. Liu, J. Lambert, C. Miyajima, E. Takeuchi, K. Takeda, and J. H. Hansen, “Riskcy action recognition in lane change video clips using deep spatiotemporal networks with segmentation mask transfer,” in 2019 IEEE Intelligent Transportation Systems Conference (ITSC). IEEE, 2019, pp. 3100–3107.

[14] M. McNaughton, C. Urmson, J. M. Dolan, and J.-W. Lee, “Motion planning for autonomous driving with a conformal spatiotemporal lattice,” in 2011 IEEE International Conference on Robotics and Automation. IEEE, 2011, pp. 4889–4895.
[15] C. Chen, A. Seff, A. Kornhauser, and J. Xiao, “Deepdriving: Learning affordance for direct perception in autonomous driving,” in Proceedings of the IEEE International Conference on Computer Vision, 2015, pp. 2722–2730.

[16] D. A. Pomerleau, “Alvinn: An autonomous land vehicle in a neural network,” in Advances in neural information processing systems, 1989, pp. 305–313.

[17] U. Muller, J. Ben, E. Cosatto, B. Flepp, and Y. L. Cun, “Off-road obstacle avoidance through end-to-end learning,” in Advances in neural information processing systems, 2006, pp. 739–746.

[18] M. Bojarski, D. Del Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang et al., “End to end learning for self-driving cars,” arXiv preprint arXiv:1604.07316, 2016.

[19] H. Xu, Y. Gao, F. Yu, and T. Darrell, “End-to-end learning of driving models from large-scale video datasets,” arXiv preprint, 2017.

[20] A. E. Sallab, M. Abdou, E. Perot, and S. Yogamani, “Deep reinforcement learning framework for autonomous driving,” Electronic Imaging, vol. 2017, no. 19, pp. 70–76, 2017.

[21] A. Kendall, J. Hawke, D. Janz, P. Mazur, D. Reda, J.-M. Allen, V.-D. Lam, A. Bewley, and A. Shah, “Learning to drive in a day,” in 2019 International Conference on Robotics and Automation (ICRA). IEEE, 2019, pp. 8248–8254.

[22] S. Bahua, “Evolution of an artificial neural network based autonomous land vehicle controller,” IEEE Transactions on Systems, Man, and Cybernetics-Part B: Cybernetics, vol. 26, no. 3, pp. 450–463, 1996.

[23] J. Koutník, G. Cuccu, J. Schmidhuber, and F. Gomez, “Evolving large-scale neural networks for vision-based reinforcement learning,” in Proceedings of the 15th annual conference on Genetic and evolutionary computation. ACM, 2013, pp. 1061–1068.

[24] K. Makantasis, M. Kontorinaki, and I. Nikolos, “A deep reinforcement learning driving policy for autonomous road vehicles,” arXiv preprint arXiv:1905.09046, 2019.

[25] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, pp. 529–533, 2015.

[26] P. E. Hart, N. J. Nilsson, and B. Raphael, “A formal basis for the heuristic determination of minimum cost paths,” IEEE transactions on Systems Science and Cybernetics, vol. 4, no. 2, pp. 100–107, 1968.

[27] B. Osinski, A. Jakubowski, P. Milos, P. Ziecina, C. Galias, and H. Michalewski, “Simulation-based reinforcement learning for real-world autonomous driving,” arXiv preprint arXiv:1911.12905, 2019.

[28] Sentdex, “Carla-rt,” https://github.com/Sentdex/Carla-RL, 2020.

[29] A. Dosovitskiy, G. Ros, F. Codevilla, A. Lopez, and V. Koltun, “Carla: An open urban driving simulator,” arXiv preprint arXiv:1711.03938, 2017.