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Evolutionary End-to-End Autonomous Driving Model with Continuous-Time Neural Networks

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***Abstract*—The end-to-end paradigm has gained considerable attention in the field of autonomous driving due to its anticipated performance. However, prevailing end-to-end paradigms predominantly employ one-shot training using imitation learning, resulting in models lacking evolutionary capabilities and struggling to adapt to long-tail scenarios. Furthermore, addressing these long-tail scenarios necessitates end-to-end models to simultaneously exhibit the generalizability of environmental representations and the robustness of control policies. Therefore, this paper proposes an end-to-end autonomous driving model called GPCT, using a Generative Perception network and a Continuous-Time brain neural network, with a Policy-Reward-Data-Aggregation (PRDA) mechanism. Specifically, the generative perception network extracts two-dimensional and three-dimensional perceptual information from monocular camera inputs and undergoes distribution fitting and sampling to obtain environmental dynamics information. Subsequently, the sequential temporal environmental dynamics information is fed into continuous-time brain neural networks to output the control information. The end-to-end model is then applied to on-policy scenarios using the PRDA mechanism to collect data for further training and evolution. Data is collected within the Carla simulator, followed by model training, and the utilization of a multi-round PRDA mechanism for data collection and training to facilitate model evolution. The algorithm's performance improves by 63.85% after five evolution experiments. In the transfer experiments, the proposed algorithm achieves a route completion rate close to 100% and maintains a driving score of around 60%, even surpassing the performance of systems equipped with multiple cameras and LiDAR. Furthermore, under heavy fog conditions, the route completion rate remains at 85%, showcasing generalizability and robustness.**

***Index Terms*—End-to-end autonomous driving, continuous-time neural networks, evolutionary method, generative model**

I. Introduction

With the rapid advancement of artificial intelligence technology, the emergence of end-to-end autonomous driving (AD) has provided a new perspective for AD technology, becoming one of the mainstream research directions in the field [1]. In contrast to classical modular AD approaches that divide the AD task into perception, prediction, planning, control, etc. [2]–[4], the end-to-end paradigm models the entire AD task as a differentiable model, which overcomes drawbacks of the classical modular paradigm, such as error accumulation and metric dissociation.

In recent years, end-to-end AD has rapidly advanced, attracting increasing scholarly engagement and leading to the publication of a series of outstanding articles. Represented by UniAD [5], a group of end-to-end AD methods [6], [7] adopts an open-loop approach for training and validation on the nuScences dataset [8], while another group [9]–[11] employs a closed-loop approach, collecting data and conducting training and validation in the Carla simulator [12]. These methods mostly utilize multi-dimensional sensor inputs (GNSS, cameras, LiDAR, etc.), output planning or control commands, and accomplish end-to-end AD tasks through imitation learning.

The tasks of AD involve a plethora of long-tail scenarios, greatly impeding the large-scale deployment and application of the AD industry, this necessitates that end-to-end AD algorithms possess both generalizability and evolutionary capabilities.

To meet the generalizability requirements of AD tasks, end-to-end AD algorithms need to simultaneously satisfy the generalizability of environmental representations and the robustness of control policies. Humans generate robust movements and reach final goals by observing environmental geometric features and dynamic information through their eyes and interacting to evaluate them. Mimicking the human perception-control process is a feasible approach for end-to-end algorithm design. However, most current end-to-end models output control actions directly using linear networks to map features, lacking neural basis. Lechner et al. [13] draw inspiration from the neural system of nematodes in the perception-to-control process to establish Neural Circuit Policies (NCPs), a brain-like neural network controller that employs continuous-time differential equations for modeling. In terms of generalizability, interpretability, and robustness, this controller outperforms linear models [14]. Therefore, this paper proposes to construct an end-to-end AD model using a Generative Perception network and a Continuous-Time brain neural network.

On the other hand, most imitation learning methods lack evolutionary capabilities and can only employ one-shot training, especially for open-loop methods using real datasets. These open-loop methods cannot redeploy the trained model to re-collect interactive data for further model training and upgrading. However, conducting experiments in the Carla simulator precisely meets this requirement. Due to the existence

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