CLIMB: Computational Lane Identification using Multi-Objective Bayesian Optimization

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***Abstract*—Autonomous vehicles are composed of various perception technologies, among which the lane detection model serves as a key technology performing numerous roles. These include providing basic information for maintaining and changing lanes in autonomous vehicles, and developing driving route plans. Existing lane perception models improve performance by adopting additional inference processes or complex neural network structures to detect lanes even when obscured by other objects. However, this results in high computational and memory complexity during the system integration process of autonomous vehicles, thereby necessitating an appropriate neural network structure. This paper proposes a method known as CLIMB (Computational Lane Identification using Multi-objective Bayesian optimization) to address this problem, ensuring convergence to the Pareto optimum between accuracy and model efficiency. Unlike traditional methods using Bayesian optimization that maximize performance with model efficiency as a regularization or constraint term, the proposed CLIMB method leverages multi-objective Bayesian optimization to give users the choice of various neural network structures, balancing both computational efficiency and accurate lane detection. To verify the efficacy of the proposed CLIMB method, we used a publicly recognized lane detection dataset and confirmed notable performance improvement compared to previous methods.**

***Index Terms*—autonomous vehicle, Bayesian optimization, lane detection, multi-objective optimization, neural architecture optimization.**

I. Introduction

Lane detection is one of the core perception technologies in autonomous driving cars [1]. While many researchers typically believe that the problem of lane detection has already been conquered through powerful neural network-based computer vision techniques, an analysis of the performance of state-of-the-art (SOTA) models on recognized datasets reveals a lower level of accuracy than expected. In some cases, this accuracy is so low that it remains at a level where commercialization is unfeasible. To address this limited lane detection capability, autonomous vehicles have been implementing a solution based on High Definition Maps (HD Maps). These maps enable the reduction of the error between the vehicle's current position and its position on the HD Map to within 50cm. Along with the emergence of HD Maps, autonomous vehicles have reached a level where they can perceive lanes without using cameras, relying solely on the vehicle's location information. However, creating HD Maps requires significant economic and time consumption, and it has a critical drawback in that it limits autonomous vehicles to predetermined routes, such as those used by self-driving shuttle buses. Therefore, the development of lane detection modules using cameras or LiDAR is an indispensable area of research for granting higher levels of safety and autonomy to autonomous vehicles.

Why is the lane detection problem still defined as a rather challenging vision problem, despite the advancements in sophisticated neural network technology? The primary reason can be attributed to the absence of visual clues. When we think of lane detection technology, we might imagine an empty road devoid of cars or obstacles. However, the actual data acquired through the front cameras of autonomous vehicles often lacks information about the lanes due to various problems. These issues can include neighboring vehicles in adjacent lanes, obstacles, sunlight, and wear and tear that causes the road's lane markings to fade. As a result, traditional convolutional neural network techniques that work by representing appropriate features from an image become unsuitable.

In many cases, human drivers perceive lanes not by relying directly on the actual road's lane markings but by inferring from surrounding clues. They might deduce the direction of lanes based on the orientation of nearby vehicles or information about lanes they have seen previously. The actual instances of perceiving lanes strictly based on the road markings themselves are rare. In essence, the complexity of real-world conditions makes the seemingly straightforward task of lane detection surprisingly complex. Traditional approaches that might work well in controlled or idealized situations can struggle with the variability and unpredictability found in typical driving environments. Consequently, the lane detection problem remains a significant challenge that requires more nuanced and adaptable solutions.

With the recent remarkable advancements in deep learning technology, we can approach the problem of "no visual clue" in lane detection by utilizing large-scale models. Just as actual human drivers infer lanes using surrounding information, we can also employ large-scale models like visual transformers

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to represent the global information contained within driving videos. By doing so, we can expect a surprising level of performance improvement compared to traditional convolutional neural networks.

However, the perception module in autonomous driving cars is not solely about lane detection; it's part of a complex system that includes various detection modules such as human recognition, vehicle recognition, and traffic light recognition. Therefore, utilizing neural networks composed of a large number of parameters may not be seen as a significant advantage for many companies aiming for the mass production of autonomous vehicles. The complexity and resource demands of such an approach could present challenges in terms of efficiency and scalability, detracting from its practical appeal in a commercial context. Therefore, we intend to propose a new and efficient lane detection module, which we have named CLIMB (Computational Lane Identification using Multi-Objective Bayesian Optimization).

II. Proposed Method

Through the previous sections, we've understood the importance of lane detection technology and have recognized that efficiency is vital for the lane detection model in the configuration of autonomous driving car systems. In this chapter, we will explain the proposed technique, CLIMB, which utilizes multi-objective Bayesian optimization to create an efficient lane detection model. In Bayesian optimization, as with other forms of optimization, the goal is to locate the global minimum of an objective function $f(x)$, where x is a sample from the bounded subset of $\mathbb{R}^D$. What sets Bayesian optimization apart from other optimization methods is its creation of a probabilistic model for the objective function $f(x)$ [2]. Once the probabilistic model is constructed, Bayesian optimization leverages it to decide where to next evaluate the objective function within X, while also accounting for uncertainty. Unlike methods that heavily rely on local gradient approximations, Bayesian optimization uses all available information from previous evaluations of $f(x)$. This enables it to find the global optimum of complex non-convex and non-differential functions with relatively few evaluations. A Gaussian process is typically used as the probabilistic model in this context, chosen for its favorable statistical and computational properties. In addition, to identify the next point for evaluation, an acquisition function must be defined. This function, which might include criteria such as probability improvement and expected improvement, quantifies the expectation of the global optimal point, guiding the optimization process.

Existing techniques using Bayesian optimization for neural architecture search typically define the problem either as a constraint optimization problem or as an optimization problem employing a regularization term. For example, in an optimization problem aiming to maximize lane detection performance, user-defined memory or computational complexities can be characterized as inequality constraints [3], or they can be utilized as penalty terms [4]. This approach allows for the balancing of performance goals with practical considerations related to resources and computational efficiency. While existing methodologies have achieved an impressive level of neural architecture search performance, they may result in the unstable convergence of Bayesian optimization or define the global optimal solution at a level that does not meet the user's desired standards. Therefore, we utilized the CLIMB technique based on Multi-Objective Bayesian Optimization as proposed in Meta Research [5]. By setting lane detection performance and model efficiency as individual objective functions, we have provided an optimal model solution that balances both these critical aspects.

TABLE I
Comparison on TuSimple

Method	F1 score	Accuracy	FLOPs
[3]	86.38	93.43	1.87E7
[4]	85.74	92.46	1.79E7
CLIMB	**87.27**	**93.77**	**1.58E7**

To analyze the performance of the proposed technique, we utilized the Tusimple dataset [6], one of the simplest among lane detection datasets, and the model we sought to optimize was UFLD (Ultra Fast Lane Detection) [7]. UFLD employs a simple neural network structure composed of residual blocks, and its learning objective function is structured around a straightforward ordinal classification. This allowed for the acquisition of fair experimental results. Table 1 lists the experimental results, and we can confirm that the proposed CLIMB achieves higher performance and model efficiency compared to existing neural architecture search techniques.

III. Conclusion

CLIMB is a lane detection optimization technique that utilizes multi-objective Bayesian optimization, and its effectiveness has been proven through the experiments conducted in this paper. Not only can it positively impact the system integration perspective of autonomous driving vehicles, but it is also easily applicable to other perception modules.

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