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Jihun Kim, Jonghong Kim, Gil-Jin Jang, Minho Lee

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Fast Learning Method for Convolutional Neural Networks Using Extreme Learning Machine and Its Application to Lane Detection

Jihun Kim, Jonghong Kim, Gil-Jin Jang and Minho Lee*
School of Electronics Engineering, Kyungpook National University

1370 Sankyuk-Dong, Puk-Gu, Taegu 702-701, Korea

*Corresponding Author: Tel: +82-53-950-6436, E-mail: mholee@gmail.com

Abstract

Deep learning has received significant attention recently as a promising solution to many problems in the area of artificial intelligence. Among several deep learning architectures, convolutional neural networks (CNNs) demonstrate superior performance when compared to other machine learning methods in the applications of object detection and recognition. We use a CNN for image enhancement and the detection of driving lanes on motorways. In general, the process of lane detection consists of edge extraction and line detection. A CNN can be used to enhance the input images before lane detection by excluding noise and obstacles that are irrelevant to the edge detection result. However, training conventional CNNs requires considerable computation and a big dataset. Therefore, we suggest a new learning algorithm for CNNs using an extreme learning machine (ELM). The ELM is a fast learning method used to calculate network weights between output and hidden layers in a single iteration and thus, can dramatically reduce learning time while producing accurate results with minimal training data. A conventional ELM can be applied to networks with a single hidden layer; as such, we propose a stacked ELM architecture in the CNN framework. Further, we modify the backpropagation algorithm to find the targets of hidden layers and effectively learn network weights while maintaining performance. Experimental results confirm that the proposed method is effective in reducing learning time and improving performance.

1 Introduction

According to the European Accident Research and Safety Report 2013," more than 90% of driving accidents are caused by human error [Truck, V, 2013]. Recently, more cars have been equipped with advanced driver assistance systems (ADASs) to assist drivers in recognizing dangerous situations. Among the functions of the ADAS, lane departure warning and lane change assistance are most relevant to these situations [Tapia-Espinoza, R., & Torres-Torriti, M., 2013].

In general, lane detection consists of preprocessing and detection. A simple and well-known method for detecting lanes is random sample consensus (RANSAC) [Kim, ZuWhan, 2008], which can identify straight lines by combining scattered and neighboring points in image scenes. However, RANSAC frequently becomes unreliable as complexity and illumination in road scenes for instance in cases with shadows, occlusions, and curves. To address these difficult cases, convolutional neural networks (CNNs) [LeCun, Yann, et al., 1998] have been implemented to enhance input images and extract regions of interest (ROIs) before performing RANSAC [Kim, J., & Lee, M, 2014].

A CNN is an effective solution in classification and recognition problems for large datasets, such as ImageNet. In contrast with other learning algorithms, a CNN has characteristics such as a local receptive fields and shared weights. A receptive field exploits the sparse connectivity of neurons to only a local region of an adjacent layer. In shared weights, replicated units create a feature map using shared parameters and increase robustness, which is efficient in lane detection problems that include different road environments.

The integration of CNN and RANSAC leads to an acceptable result with complex road scenes. However, several problems remain in lane detection tasks. The first problem is the limited training data available for complex road