A Training Method of Convolution Neural Network for Illumination Robust Pedestrian Detection

Junmo Jeong, Dept. of electronics Engineering, Seokyeong University, Seoul, Korea

ABSTRACT

In this article, the authors propose a new training method of convolution neural networks for pedestrian detection under the illumination of robust environments of ADAS (Advanced Driver Assistance System). This training method was aimed at proposing a method to increase the recognition rate in a system that classifies objects by receiving distorted images in real time as the ADAS, by using the Convolution Neural Network (CNN). The proposed method used images with an increased distortion level by setting gamma to 0.7, and the conventional method was experimented with images with a gamma set to 1. In this article, the authors experiment with the comparison of the conventional training method using the preprocessing accelerator and the proposed training method using the gamma variation. In this study, pedestrian images with a distorted illumination intensity were used in training and then the accuracy of pedestrian classification was tested with normal images and distorted images as test images. The proposed method shows an error rate of 9.8%, which was improved by 1.2% in accuracy.

KEYWORDS
Backpropagation, Convolution Neural Network, Illumination Robust, Image distortion, Pedestrian Detection, Training

INTRODUCTION

Although the artificial intelligence has been expected to have the much more accurate and faster context recognition ability than humans for a long time, the inadequate computing power has restrained its implementation. However, the rapid increase of computing power and the growing demand for various context recognitions made deep learning, which is a type of artificial intelligence, possible. As the object recognition technology using deep learning has quickly advanced, the context recognition technique using images has been applied in wide ranging areas.

The key technology for self-driving car is the object recognition and context recognition using sensor and image data. The technology requires the ability to drive, stop and park the cars with better decision-making capability than human even under the difficult road environment and poor weather situations such as rain, fog, snow and low lighting. The ADAS (advanced driver assistance system) technology currently applied in self-driving cars provides only the simple warning and braking function through object recognition and depends on driver’s judgment in a complex situation. However, the more accurate and faster context recognition in a complex and poor environment must be reflected in the ADAS technology for the self-driving function to replace human driving. As such, many recent studies have focused on deep learning to improve the context recognition capability and the
preprocessing capability of poor image data for the ADAS technology to have such capability (Fukui, Yamashita, Yamauchi, Fujiyoshi & Murase, 2016; Nedevschi et al., 2008).

The preprocessing technology of image data obtained from cameras is essential to work with high quality data in poor road condition and weather environment. The preprocessing technology prevents wrong judgment by improving the object recognition technology of ADAS. Thus, deep learning can greatly improve the accuracy of object and context classification using imaging. Many recent studies and experiments have proven the efficiency of CNN (convolutional neural network) in deep learning as a way to classify objects and contexts (Farabet, Martini, Akselrod, Talay & LeCun, 2010). There’s a great opportunity to use CNN techniques to further enhance vehicle vision applications to achieve high level of accuracy. But high-resolution imaging is so sophisticated that we’re relying on it for everything for the autonomous vehicle of the future (Sochor, Herout & Havel, 2016; Liao et al., 2015).

ADAS needs to maintain the performance despite various weather’s changes, like rain and light. Because the conventional CNN based ADAS use the memory for storing the weights learned previously, they can’t use the optimized weight accommodated to the weather’s change. Namely, the new training can’t be adapted in real time. Therefore, the conventional CNN based ADAS has a disadvantage in a performance depending on the status of input images. For solving such a problem, the conventional CNN based ADAS puts the pre-processing accelerator for improving the image quality before entering a CNN based image classification (Krizhevsky, Sutskever & Hinton). Such as a hardware accelerator is great pressure on the ADAS because of a huge hardware configuring the ADAS.

We propose the training method of convolution neural network with a distorted image instead of using a huge hardware for revising the distorted input image. This training method has the CNN based ADAS showing the low error rate under the high contrast. This provides a significant level of adaptability to weather changing environments, reducing hardware complexity. In this paper, we experiment the comparison of the conventional training method using the preprocessing accelerator and the proposed training method using the gamma variation (Jeong, 1977, pp. 19-21).

RELATED RESEARCHES

Convolution Neural Network

Since the CNN uses the method of classifying target objects using the features included in the input images, it is divided into a part that find the features and a part that evaluates them (Krizhevsky, Sutskever & Hinton; Jia et al., 2014). For some target objects, the input image is divided into smaller images using a filter, and the needed features are evaluated using the small image obtained through repetition. The number of feature maps increases according to the number of features needed for evaluation, and the extracted feature values are enhanced through max pooling (Boureau & Ponce, 2010). The enhancement by repeating the feature evaluation is needed to increase the evaluation accuracy. However, repeating the feature evaluation increases the depth of CNN thus greatly increases the processing time and size of CNN. Therefore, a separate classifier may be used instead of increasing repetitions. The classifier determines the target object by comparing the pre-learned values and the extracted feature values. Since the accuracy of classifier mostly depends on the pre-learned value, the accurate learning is very important. This purpose of this study is to improve the accuracy of learning since it can decrease the depth and evaluation accuracy of CNN (Zhang et al., 2015).

The weight and activation function play the important role in extracting and classifying the features in CNN. The weight represents the importance of convolution result using filter, and its value is gradually enhanced through learning. The capability of CNN is determined by the initial weight value and accuracy of learned value and depends on parallel processing capability of memory that stores the weight during a CNN design. The activation function makes the final evaluation using the
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