

Chapter 15

Multiple Flames Recognition Using Deep Learning

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ABSTRACT

Identifying fire flames is based on object recognition which has valuable applications in intelligent surveillance. This chapter focuses on flame recognition using deep learning and its evaluations. For achieving this goal, authors design a Multi-Flame Detection scheme (MFD) which utilises Convolutional Neural Networks (CNNs). Authors take use of TensorFlow in deep learning with an NVIDIA GPU to train an image dataset and constructed a model for flame recognition. The contributions of this book chapter are: (1) data augmentation for flame recognition, (2) model construction for deep learning, and (3) result evaluations for flame recognition using deep learning.

INTRODUCTION

Nowadays, flame identification has become one of the most popular topics in the field of visual object recognition (Jiao, et al., 2011; Wang, et al., 2018; Ren, et al., 2018; Wang, et al., 2017; Lu, et al., 2017; Gu, et al., 2017). It has a myriad of valuable applications in monitoring and surveillance for public security and safety. In this book chapter, we aim to develop a computational tool that could detect various types of flames automatically and classify the flames from input visual data. A reliable recognition requires a well-designed deep neural network. Our human visual system recognizes objects based on long-term training from our ordinary life. When the visual object is relatively complicated, we usually infer it based on our human experience (Yan, 2017).

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For object classification, the output usually is class categories. In real scenarios, because of various reasons, our human vision sometimes even finds it is hard to recognize flames correctly (Gupta, Agrawal, Yamaguchi, 2018). If we use a computer to classify the flames quickly, the recognition rate by using machine learning algorithms will be low and could not achieve the expected goal of flame recognition.

The experimental results of traditional machine learning are mostly based on well-prepared and specific image datasets (Jiao, et al., 2011). Lighting/shielding variations of flames are much less than the ones in real scenarios. Moreover, appearance or shape of a flame is continuously changing, images of the same flame at different viewing angles are quite distinct. Therefore, the accuracy of flame recognition is rather lower than that we expect (Erhan, et al., 2014).

Hence, in this chapter, we propose the model: SSD (Liu, et al., 2016). Flame detection can be considered as a subject of flame recognition. We split our task of flame recognition into two categories (1) flame classification, (2) flame detection and locating. The feature maps firstly are extracted from input images using CNN operations, which are used as the input of deep neural networks for classification and identification. Using deep learning (LeCun, et al., 2015), the recognition accuracy will be greatly improved; it can enhance the robustness of flame recognition tremendously (Erhan, et al., 2014).

Since LeCun et al. have designed and trained a ConvNets (LeCun, Huang & Bottou, 2004) which used an error gradient-based algorithm (LeCun, et al, 1989); much excellent performance has been achieved in the field of pattern recognition. Also, the convolutional network has been proved to be effective (Luo, et al., 2017). At present, deep learning is successfully applied to various applications, such as document analysis, face detection, voice detection, license plate recognition, digital handwriting recognition, human motion recognition, and human face recognition (Zheng, et al., 2018).

In this chapter, we adopt CNN model to create a new neural network so as to recognize fire flames in depth. Also, this method could avoid the complexity that the traditional methods have. Our algorithm for flame recognition is implemented in the primary method CNN. We train the model with our image dataset assisted by using the GPU-based platform TensorFlow. We employ NVIDIA GTX 980M GPU to accelerate the computations of our experiments. Training with GPU is much efficient. By cropping flame regions from each frame in a recorded video, we collect these images and used them as our dataset. Also, we manually labeled the images having the flame regions.

This chapter is organized as follow. Related work is presented at Section 2, our method is described in Section 3. Our results and analysis are demonstrated in Section 4, the conclusion will be drawn in Section 5.

RELATED WORK

The performance of flame recognition primely depends on the flame classifiers (Jiao, et al., 2011). Thus, we require a classifier having high accuracy and low false alarm ratio. Most of video-based fire detection techniques devoted to flame detection so as to provide an early fire alarm. Traditional ultraviolet and infrared fire detection has a great deal of disadvantages. With too many influencing factors, an errant alert or false alarm is easily to be generated. At the same time, location, size, and growth rate of fire flames may also be wrong.

Due to these problems, a technology has been developed for video capturing and fire flame detection automatically by analyzing the streaming visual data. This algorithm is based on spectral, spatial, and temporal features of fire flame (Healey, et al., 1993). In 1994, digital image processing was used

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