Athlete Number Plate Application Based on Deep Learning Image Recognition

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Abstract. With the increasing popularity of sports competitions, the recognition of number plate images has become a label for athletes in order to make it easier to monitor their progress and status in real time. This paper proposes a comprehensive deep convolutional neural network model for number plate recognition. The model is divided into three modules: the localization of the number plate, the pre-processing of the number plate and the character recognition. Deep learning algorithms were applied to number plate localization for high accuracy, number plate pre-processing using image enhancement techniques, projection methods for character segmentation, and finally a model combining multiple templates and BP neural networks for character recognition. Better results and potential for athlete number plate recognition is provided by the model proposed in this study. Further work is planned to test the robustness of the model in more complex scenarios and to apply it to real-world scenarios to provide more accurate number plate recognition for sporting events.

Keywords: Deep Learning, Racing Bib Number Recognition, Numberplate Localization

1 Introduction

With a wide variety of sporting events on the increase and a large-scale development trend. Thousands of photos of athletes during the event are stored in the image library for each race. It is a huge challenge to find information about a specific athlete in a large number of images. They are highly influenced by environmental factors due to the low accuracy of traditional identification methods. It is hoped that a fast and accurate number plate recognition system can be developed to identify athletes' number plates more accurately and quickly to assist referees, spectators and athletes in regulating their own behavior.

Athlete number plate recognition is the use of digital image processing and pattern recognition to extract and identify the number plate, widely used in various types of events [1]. Deep learning is a complex type of machine learning algorithm [2]. It is adept at solving pattern recognition problems in diverse environments. It extracts

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image features through layering, using texture, edge, color and other information in the image to predict where the target might be in the image. This process overcomes the problems associated with traditional methods of extracting image features by automatically learning the features from the samples [3], rather than manually designing the features. Region localization, character segmentation and character recognition are the main components of number plate recognition. Methods based on greyscale image features and color images are commonly used to localize number plate areas [4]. Acquired images of athletes usually contain a lot of unrelated background. Number plate recognition requires the elimination of such irrelevancies and the localization of the license plate region important to the character recognition process. Frequently used methods for character segmentation include template matching [5], projection [6] and connected region [7]. The image should be pre-processed before character segmentation, as the number plate positioned may have uneven light and tilt problems due to the influence of shooting light, shooting angle, etc. Common character recognition techniques include template matching, OCR, SVM and so on [8].

A comprehensive deep convolutional neural network model for license plate recognition is proposed in this paper, based on an analysis of current license plate recognition difficulties. The work will be important for the further enhancement of the accuracy and robustness of athlete number plate recognition and the advancement of related fields.

2 Material and Methods

2.1 Dataset Description

The composition of the experimental dataset of athletes' bibs in this paper is mainly derived from photos of runners' public participation taken from marathon websites. The collection of photos fulfils the conditions: (1) Various races in various areas; (2) Taken from different locations within the same field, including the finish line as well as the race; (3) Photographs taken by athletes in different atmospheric conditions; (4) Sharply focused and blurred photos; 2500 images are selected as the dataset and each image contains the information of the athlete's number plate, which is divided into a training set and a test set in a ratio of 7:3. A random sample of 1500 license plate photos was selected due to the small number of publicly available license plate recognition datasets for athletes. The athletes' photos and a subset of the number plate dataset were shown in the Figure 1.

Fig. 1. Athletes' photos and the number plate dataset (photo credited: original)

2.2 Convolutional Neural Networks (CNN)

CNN is one of the leading deep learning algorithms and is widely used in image processing. Following the proposal of the AlexNet network by Krizhevsky et al. in 2012 [9], the development of convolutional neural network related techniques has accelerated [10-13], establishing the position of convolutional neural network based related techniques in deep learning applications. The CNN consists of the following layers: input, convolution, pool, full connection, activation function and output. Figure 2 illustrates the CNN model.

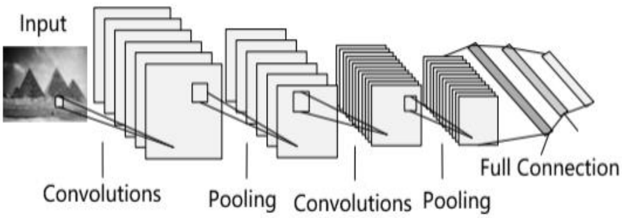

Fig. 2. Example of CNN Model [14]

Input Layer. The captured image is fed into a convolutional neural network for feature extraction from the original image, which can be multi-channel.

Convolutional Layer. This means that the convolution kernel will be moved to all positions on the image, and at each position the template will be convoked with the image. Each convolution layer can generate a set of feature maps, where the first convolution layer may only be able to extract a few low-order features such as edges, lines, and so on, while the network of each subsequent convolution has a significantly higher feature extraction capability than the first network and is able to extract more complex and higher order features that cannot be extracted by the first layer [15].

$$X_j^l = {}_{i \in M_j} X_j^{l-1} * K_{ij}^l + b_j^l \tag{1}$$

Where K_{ij}^l is the convolution kernel in eq. X_j^i is the first map of feature j after the convolution. b_j^l for the bias parameter. M_j is the set of feature maps used for the selection of the input image.

Pooling Layer. In order to retain the most significant features of the image and improve the speed of the network, the pooling layer is used to downscale the features extracted from the convolutional layer. The main types of pooling are Max Pooling and Mean Pooling [16].

Fully Connected Layer. Data from previous layers is integrated, and all activation data from previous layers is input to the fully connected layer, which ultimately outputs a one-dimensional feature vector.

2.3 Image Enhancement

When the image is captured, it is affected by the environment, resulting in blurring, distortion and lack of focus, and when it is transferred, it is affected by electronic noise, making it difficult to segment and recognize characters. To improve image quality, Image Enhancement is often used [17]. Image Enhancement can improve the quality of an image by clarifying blurry images, enhancing specific information in the image while reducing or removing undesired information [18], and increase character recognition accuracy. Filtering, sharpening and grey level adjustment can be used to enhance the image.

Spatial Filtering. Spatial filtering is a widespread image enhancement technique that uses the spatial information of the image itself to filter the image to improve the quality and appearance of the image. Mean, Median and Gaussian filtering are some of the most widely used spatial filtering methods. Mean filtering replaces the grey value of each pixel in an image with the average of its surrounding pixels, effectively removing noise from the image while blurring the edges. Median filtering is ideal for removing very high levels of noise, such as pepper noise, by sorting pixel values in a window from smallest to largest and then using the median as the new pixel value. Gaussian filter is a smoothing function that calculates each pixel's grey value and its neighbor's grey value by a certain weight, which can effectively eliminate high-frequency noise and preserve fine image information.

Histogram Equalization. The principle of histogram equalization is to change the original image's greyscale histogram from being concentrated in one greyscale interval to being evenly distributed across the range. It is a non-linear stretching of an image so that the number of pixels in a given greyscale range is approximately equal [19]. This can enhance low contrast or overexposed images by giving the image a wide dynamic range of grey tones and high contrast.

Image Sharpening. The purpose of image sharpening is to enhance an image's edges or contours. Sharpening techniques include first-order differential sharpening and second-order differential sharpening. The most frequently used method is the gradient method. In discrete image processing, the gradient is represented by a difference approximation. The Robert, Sobel, Prewitt, Laplacian, etc. operators are commonly used in the gradient sharpening method [19]. Equations (2) and (3) denote the difference form of the first order differentiation and the difference form of the second order differentiation, respectively [19].

$$\frac{\Delta f}{\Delta x} = f(x+1) - f(x) \tag{2}$$

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x+1) - 2f(x) \tag{3}$$

2.4 Method of Character Recognition

Character recognition is mainly based on template matching, artificial neural networks, etc. Template matching involves either directly matching the characters to the template or extracting the features of the characters and matching these to the template. Direct comparison with the template requires resizing the characters to the standard template size, and then comparing the characters to the template. However, since the image has been pre-processed and normalized, the greyscale of the images or the location of the pixels is usually altered, affecting recognition performance. This method involves extracting a set of characteristics from the character image to be recognized and comparing them with the corresponding characteristics in the template library to obtain a recognition output [1]. The BP neural network is a multilayer back-propagating network with continuous transfer function, which has a simple structure and has been widely used as a mathematical model for nonlinear uncertainty [20]. The model in this paper combines multi-template and BP neural networks. This template matching technique rapidly identifies and outputs simple and easy-to-read signs, and feeds more complex signs into the BP neural network. Figure 3 represents the algorithmic structure for combining templates and BP neural networks.

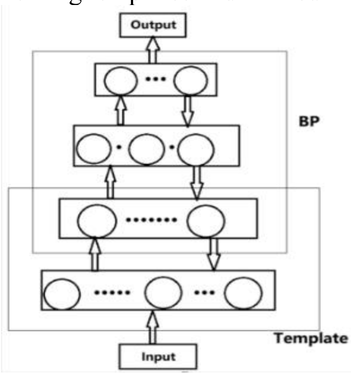

Fig. 3 algorithmic structure [20]

3 Result and Analysis

3.1 Number Plate Locator

Most of the traditional positioning of the number plate is done by means of the color characteristics of the number plate. The plate area can be detected by exploiting the fact that there is a significant difference between plate color and background color. However, this method is easily affected by the shooting environment, shooting angle and distance, which ultimately results in inaccurate positioning. CNN is used for number plate localization in this paper. The extraction of the candidate regions is first carried out on the input image. The region is then fed into the network that will be used for the extraction of the region's features. These extracted characteristics are fed into a classifier, which classifies and filters out number plates and backgrounds. The constructed CNN consists of three convolutional, three pooling, one fully connected and one softmax classification layer. To extract the features of the candidate region, the size of the candidate region is normalized to 32*32 and then input into the network. Multiple convolutional kernels are used to abstract features from the image. A CNN structure diagram was presented in Figure 4.

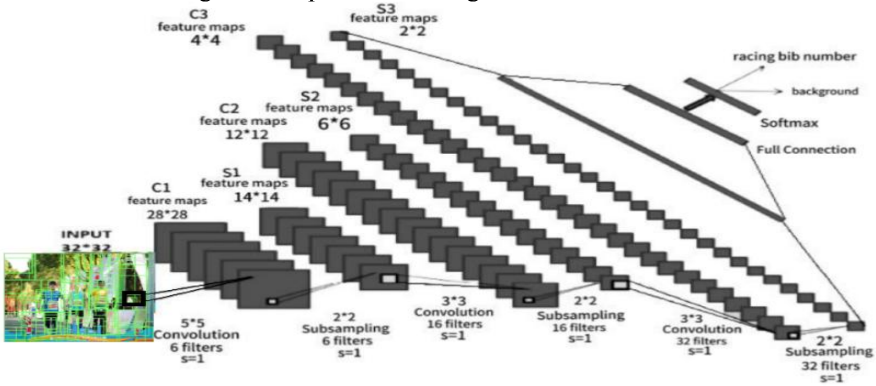

Fig. 4. CNN Structure Diagram (photo credited: original)

To demonstrate the effectiveness of the recognition, the results of the proposed method are compared with those of a conventional recognition method, which relies on manually extracted characteristics. It is noticeable that the region appears to overlap heavily with the background, since conventional location is based on both color features and the extraction of morphological parameters. There is a clearer segmentation and better differentiation from the background of the number plate region obtained after deep learning. After convolution, pooling and classification, it allows for a precise localization. Number plate recognition based on deep learning can, to a certain extent, overcome the interference caused by background noise and complete the number plate recognition process more accurately. A total of 2500 images of number plates have been tested under the same conditions. The evaluation criteria are the correct and incorrect localization rates. Images that fail to be recognized are also counted as incorrect localizations. The correct localization rate of this paper's method is as high as 93.76%, while the correct localization rate of morphological feature-based method is only 86.45%, proving the superiority of this paper's method. The traditional localization was shown in the Figure 5, and Figure 6 showed CNN recognition.

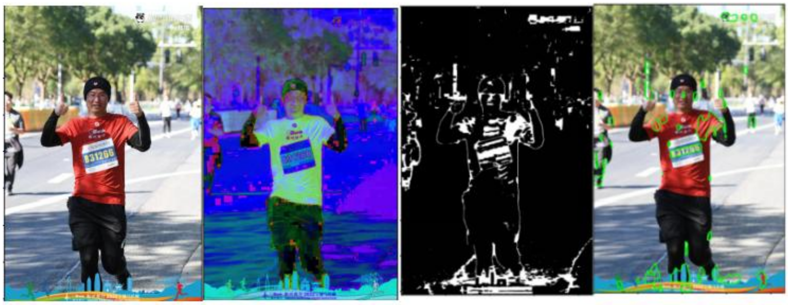

Fig. 5. Traditional Localization (photo credited: original)

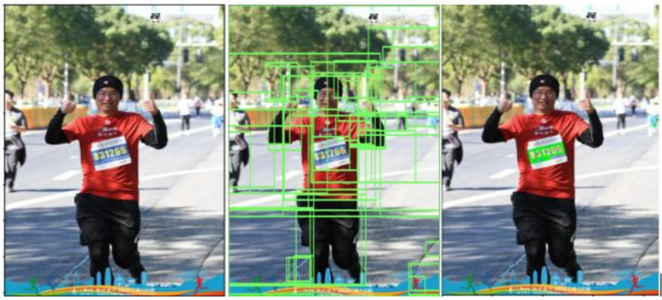

Fig. 6. CNN Recognition (photo credited: original)

3.2 Number Plate Pre-processing

To complete the identification of the athlete's number plate, once the number plate has been positioned, the characters on it must be segmented, accurately identified and then subjected to character recognition. Because of possible interference of background color and lighting conditions, the positioning of the number plate may result in irregular illumination and blurring, and the angle and lighting of the shot may result in the number plate being out of focus. All of them will affect the correct segmentation of characters. Thus, pre-processing of the localized plate region is required to improve plate recognition.

Spatial Filtering. Due to the limitations of shooting conditions and the effects of equipment during transmission, noise is introduced into the image. Comparison of three spatial filters, mean, median and Gaussian. When it comes to removing points of high frequency noise from images, Gaussian filters are considered to be more effective. Figure 7 showed the spatial filtering.

Fig. 7. Spatial Filtering (photo credited: original)

Histogram Equalization. Variations in the greyscale can be altered by adjusting the brightness or contrast of the pixels in the image. Histogram equalization balances out the pixels and increases the contrast and sharpness of the image. With the help of adaptive histogram equalization, the image contrast can be improved without an excessive increase in the overall color distortion of the image. The histogram equalization has been shown in the Figure 8.

Fig. 8. Histogram equalization (photo credited: original)

Image Sharpening. For image edge detection and enhancement of high frequency components of edges to improve clarity and detail, a Laplace filter and Sobel operator is often used. Figure 9 displayed the image sharpening.

Fig. 9. Image Sharpening (photo credited: original)

After comparing different image enhancement methods, the Gaussian filter is used to denoise the image and smooth the image structure, enhances the image features by adaptive histogram equalization and finally goes through Sobel operator for edge detection.

Character Segmentation. The regional number plate image is pre-processed for character segmentation. The projection method for the segmentation of number plate characters will be the subject of this paper. To calculate the sum of pixels for each column and row, the binary image is projected horizontally and vertically. Character regions are followed by an analysis of the projection histograms, which identifies the spike in each letter and the position of the segment between the letters. Figure 10 showed how the characters get segmented.

Fig. 10. Character recognition result (photo credited: original)

Once the number plate region localization, pre-processing and character segmentation have been completed, the final critical step in number plate recognition is to recognize the segmented characters. It combines template matching and BP neural networks to reduce template matching segment size and use the BP network for more sophisticated character recognition. The results of the character recognition were shown in Figure 11.

Fig. 11. Character recognition results (photo credited: original)

4 Conclusion

In conclusion, deep learning has greatly improved the efficiency of number plate recognition as a method capable of extracting abstract features from images. This paper proposes and implements a comprehensive deep convolutional neural network model for athlete number plate recognition. The module is structured into number plate localization, number plate pre-processing, segmentation, and number plate recognition. Existing localization methods rely on traditional manual feature extraction, which is unsatisfactory due to strong environmental influences. In this paper, the CNN model, which is more robust in complex environments, is used for the automatic extraction of features for number plate recognition. To achieve superior denoising results, several image enhancement techniques are used simultaneously to optimize the pre-processing results. Finally, the character recognition module was completed using image segmentation, character normalization, multiple templates and BP neural networks. Deep learning technology is more accurate in recognizing images of athletes' number plates than traditional recognition technology. This research will have a significant impact on the efficiency of sports organizations and the enhancement of the spectator experience at sporting events. By automatically recognizing athletes' number plates, the system can reduce errors and manual intervention, improve accuracy and provide real-time results for the competition. As science and technology continue to advance, the application and expansion of image recognition technology supported by deep learning methods is expected to grow exponentially in the field of competitive sports image recognition.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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