Cat Face Detection Based on Haar Cascade Classifier

Xingxing Li

Department of electronics and information engineering, Guangzhou College of Technology and Business, FoShan, 528138, China

lixingxing_Edooy@163.com

Keywords: Cat Face Detection, Haar Feature, Cascade Classifier

Abstract: Cat face recognition technology is widely used in industry at present, and the most important and initial step is the need for cat face detection. This paper uses Haar feature to extract features of cat face, calculates Haar rectangular eigenvalue-integral graph quickly, and screens effective rectangular features for classification and recognition. Using AdaBoost classifier to transform weak classifier into strong classifier can effectively detect cat face.

1. Introduction

Cat face detection is a classical problem deeply studied in the field of machine vision. It has important application value in pet detection, pet raising and other fields. In the process of cat face recognition, cat face detection is the first step of the whole cat face recognition algorithm. Early face detection algorithms used template matching technology, that is, a face template image is matched with each position in the detected image to determine whether there is a cat face at this location; after that, machine learning algorithm is applied to this problem, including neural network, support vector machine and so on. All of the above are based on the recognition of face-non-face binary classification in an area of the image. The early representative achievement is the method proposed by Rowley et al. [1, 2]. They used neural networks for face detection, and trained a multi-layer perceptron model with 20×20 face and non-face images. Document [2] solves the problem of multi-angle face detection. The whole system consists of two neural networks. The first network is used to estimate the angle of the face, and the second one is used to judge whether the face is human or not. The angle estimator outputs a rotation angle, then rotates the detection window with the whole angle, and then uses the second network to judge the rotated image to determine whether it is a face or not. Haar [3] feature is an image feature descriptor used for target detection or recognition. Haar feature is usually combined with AdaBoost [4] classifier to complete the classification of candidate frames. These classifiers form a pipeline to determine the candidate frame image in the sliding window and determine whether it is a cat face or a non-cat face

2. Feature extraction & classifier

2.1 Haar feature extraction

The Haar-like feature is the sum of the pixel values in the white rectangular box, minus the sum of the pixel values in the black area. As an example, the first feature in Figure 1 is calculated as follows: first, the sum of all the pixels in the white rectangular area on the left is calculated, then the sum of all the pixels in the black rectangular area on the right is calculated, and finally the Haar-like feature value is the sum of the left and the right. This feature captures the edge, change and other information of the image. Various features describe the change information of the image in various directions. The facial features have their own brightness information, which is very consistent with the characteristics of Haar-like features.

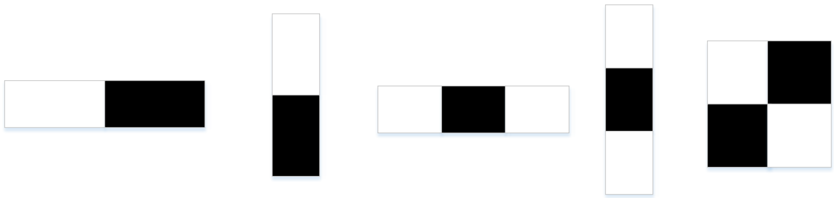

Figure 1. Diagram of Haar-like features

In order to achieve fast computation, a mechanism called Integral Image is used. The sum of the pixels of any rectangular region in the image can be calculated quickly by integral graph, and various types of Haar-like features can be calculated. Suppose there is an image whose pixel value is $(\overline{x_{ij}})$ in column i of row j. The integral graph is defined as: $s_{ij} = \sum_{p=1}^{i}\sum_{q}^{j} x_{pq}$, which i s the sum of the elements in the upper left corner of the original image at any point. After constructing the integral graph, it can quickly calculate the sum of pixels in any rectangular region. Take the rectangular box in Figure 2 as an example.

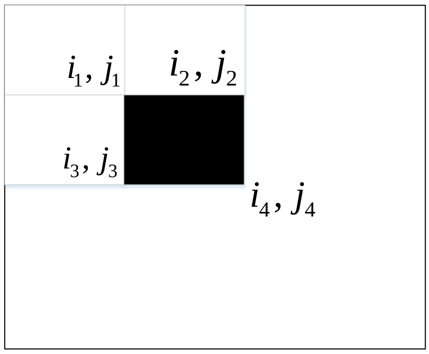

Figure 2. Integral diagram

In the figure above, the sum of the pixel values in the black rectangular box is calculated. Suppose that the coordinates of the lower right corner of the four rectangles above are:

$$(i_1,\ i_1),(i_2,\ i_2),(i_3,\ i_3),(i_4,\ i_4) \quad (1)$$

The sum of the pixel values in the black rectangular box is:

$$S_{i_4 j_4} - S_{i_2 j_2} - S_{i_3 j_3} + S_{i_1 j_1} \quad (2)$$

The reason for this is that the sum of the pixel values in the black area equals the sum of the pixel values in the four rectangular boxes, subtracting the sum of the pixel values of the two rectangular boxes above, and subtracting the sum of the pixel values of the two rectangular boxes on the left. In this way, the rectangular box in the upper left corner is subtracted twice, so it needs to be added again. After calculating the sum of the pixel values of any rectangular region, any of the above Haar-like features can be easily calculated.

2.2 AdaBoost cascade classifier

Weak classifiers use the simplest decision tree with very small depth, and even have only one internal node. The training algorithm of decision tree is not elaborated here. It should be noted that the feature vectors here are sparse, that is, each decision tree receives only a small amount of input of feature components and makes decisions based on them. The strong classifier is the same as the previous one. The difference is that the strong classifier here adds an adjustment threshold.

$$\mathrm{F(x)} = \sum_{i=1}^{N} f_i(x) - \varepsilon \quad (3)$$

where ε is the threshold, it is obtained by training. Each level of strong classifier uses all face samples as positive samples in training, and scans the negative sample images with the upper level of strong classifier. The regions identified as faces in the false alarm are intercepted as negative samples of the next level of strong classifier.

Assuming that the detection rate and false alarm rate of the class I strong classifier are di and fi respectively, the false alarm rate of cascade classifier is $\mathrm{F}=\prod f_i$, which indicates that increasing the number of classifiers can reduce the false alarm rate, and the detection rate of similar cascade classifiers is as follows:

$$D = \prod d_i \tag{4}$$

This formula shows that increasing the number of classifiers will reduce the detection rate. For the former, it can be understood as the probability that a negative sample is judged to be positive by each level of classifier; for the latter, it can be understood as the probability that a positive sample is judged to be positive by all classifiers.

After the advent of VJ algorithm, the detection problem of approximate frontal face is solved. Since then, a large number of improvement schemes have emerged, which has been the mainstream framework of face detection algorithm until the emergence of deep learning technology. The improvements of these schemes are mainly in the following aspects: new features, including extended Haar features [3], ACF features, etc. They have stronger descriptive ability than standard Haar-like features, and lower computational cost. Use other types of AdaBoost classifiers. The discrete AdaBoost algorithm is used in the VJ framework. In addition, there are real number, Logit, Gentle and other schemes. Real, Logit and Gentle AdaBoost algorithms can not only output label values, but also give confidence and have higher accuracy. A cascade structure of classifiers, such as Soft Cascade, transforms multiple strong classifiers of VJ method into a strong classifier (the algorithm will be introduced later). In addition, the detection of faces in various angles and gestures is another focus of research. The cascade of classifiers in VJ method has only one path, which is a waterfall model. The improved scheme includes tree cascade, pyramid cascade and so on.

3. Experiments

The experiment is divided into three steps:

(1) Image preprocessing: graying of original image

A cat face image is read, and the three-dimensional RGB image is normalized into one-dimensional gray image. The gray level can reflect the distribution and characteristics of the overall and local chroma and brightness levels of the whole image.

(2) Cat face detection using Haar feature cascade classifier is shown in Figure 3:

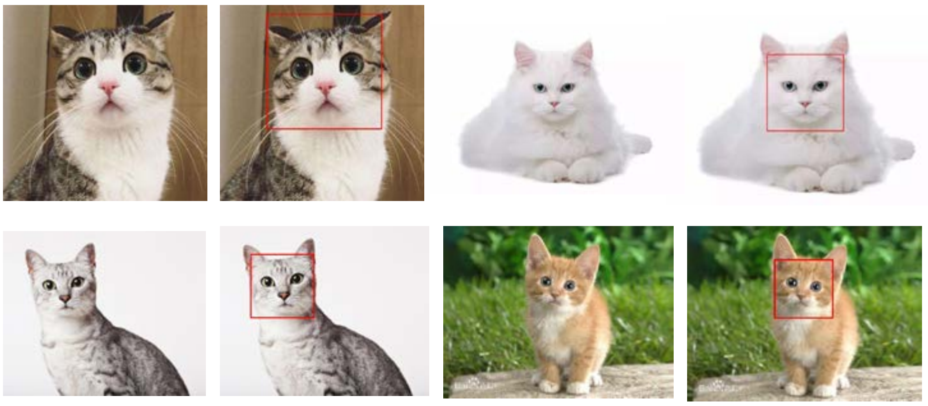

Figure 3. Cat Face Detection Results

Cat face features are more complex than face features, including many texture features, but also affected by hair color, nose bridge, eyes and many other features. Compared with face, these features are more differentiated and difficult to capture. Using Haar feature and cascade classifier can capture some edge and texture features better. Cascade classifier can change weak classifier into strong classifier, which can distinguish cat face from non-cat face.

4. Conclusion

The Haar-like eigenvalues are calculated by subtracting the sum of all the pixel values in the white rectangle of the rectangular template from the sum of all the pixel values in the black rectangle.

Haar-like feature can effectively extract texture features of images, and each template can extract feature values of different positions and scales by translation and scaling. Adaboost [4] provides a powerful mechanism to hook up weak classifiers and features, select classifiers with good performance, and assign corresponding weights. A direct way to link weak classifiers with features is to make a one-to-one correspondence between weak classifiers and features, that is to say, a weak classifier only depends on one feature.

Acknowledgments

This work was financially supported by fund project, that is, Guangzhou Institute of industry and commerce college level research project in 2019 "Research and design of S bandradio frequency front-end" KA201937.

References

[1] Rowley K M, Clubb K S, Smith G J W, et al. Right-Sided Infective Endocarditis as a Consequence of Flow-Directed Pulmonary-Artery Catheterization [J]. Survey of Anesthesiology, 1985, 29(5):292.

[2] Rowley M, Buchanan H, Mackay I. RECIPROCAL CHANGE WITH AGE IN ANTIBODY TO EXTRINSIC AND INTRINSIC ANTIGENS [J]. The Lancet, 1968, 292(7558):24-26.

[3] Wilson P I, Fernandez D J. Facial feature detection using Haar classifiers [J]. Journal of Computing Sciences in Colleges, 2006, 21(4):127-133.

[4] Zhu J, Arbor A, Hastie T. Multi-class AdaBoost [J]. Statistics & Its Interface, 2006, 2(3):349-360.