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Analysis and Interpretation Approach Representiong the Steps Of Face Recognition

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Abstract: We present a face detection method and explained the steps followed in face detection. It includes the Harr key features , rapid face detection, AdaBoost machine-learning method and cascade classifiers to combine many features of the images. Face detection is the process of detecting the location of the human face and in this paper we explained the basic concepts
Keywords: Histogram, Face Recognition, Analysis, Interpretation and Face Detection.

I. INTRODAUCTION

Human facial expression is able to disclose human's emotions, moods, attitudes and feelings etc. Recognizing expressions can help computer learn more about human's mental activities and react more sophisticatedly, therefore it has enormous potentials in human-computer interaction (HCI)[1,2,3,4]. Explicitly, the expressions are some facial muscular movements comparing to neutral face. The face detection problem is challenging as it needs to account for all possible appearance variation caused by change in illumination, facial features, occlusions, etc. In addition, it has to detect faces that appear at different scale, pose, with inplane rotations. In spite of all these difficulties, tremendous progress has been made in the last decade and many systems have shown impressive real-time performance. The recent advances of these algorithms have also made significant contributions in detecting other objects such as humans/pedestrians, and cars.[5.6.7]

II. WORKING

This approach to detecting objects in images combines four key concepts:

a. Simple rectangular features, called Haar features
b. An Integral Image for rapid feature detection
c. The AdaBoost machine-learning method
d. A cascaded classifier to combine many features efficiently

The features that Viola and Jones used are based on Haar wavelets. Haar wavelets are single wavelength square waves (one high interval and one low interval). In two dimensions, a square wave is a pair of adjacent rectangles - one light and one dark. [8,9,10].

The actual rectangle combinations used for visual object detection are not true Haar wavlets. Instead, they contain rectangle combinations better suited to visual recognition tasks. Because of that difference, these features are called Haar features, or Haarlike features, rather than Haar wavelets. Figure 1 shows the features that OpenCV uses.

The presence of a Haar feature is determined by subtracting the average dark-region pixel value from the average light-region pixel value. If the difference is above a threshold (set during learning), that feature is said to be present.[11,12,13,14] .

To determine the presence or absence of hundreds of Haar features at every image location and at several scales efficiently, Viola and Jones used a technique called an Integral Image. In general, "integrating" means adding small units together. In this case, the small units are pixel values. The integral value for each pixel is the sum of all the pixels above it and to its left. Starting at the top left and traversing to the right and down, the entire image can be integrated with a few integer operations per pixel. As Figure 2 shows, after integration, the value at each pixel location, (x,y), contains the sum of all pixel values within a rectangular region that has one corner at the top left of the image and the other at location (x,y).[15,16,17] To find the average pixel value in this rectangle, you'd only need to divide the value at (x,y) by the rectangle's area.

But what if you want to know the summed values for some other rectangle, one that doesn't have one corner at the upper left of the image? [18,19,20]Figure 2b shows the solution to that problem. Suppose you want the summed values in D. You can think of that as being the sum of pixel values in the combined rectangle, A+B+C+D, minus the sums in rectangles A+B and A+C, plus the sum of pixel values in A. In other words,
D = A+B+C+D - (A+B) - (A+C) + A.

Conveniently, A+B+C+D is the Integral Image's value at location 4, A+B is the value at location 2, A+C is the value at location 3, and A is the value at location 1. So, with an Integral Image, you can find the sum of pixel values for any rectangle in the original image with just three integer operations: (x4, y4) - (x2, y2) - (x3, y3) + (x1, y1).

To select the specific Haar features to use, and to set threshold levels, Viola and Jones use a machine-learning method called AdaBoost. AdaBoost combines many "weak" classifiers to create one "strong" classifier. "Weak" here means the classifier only gets the right answer a little more often than random guessing would[24,25,]. That's not very good. But if you had a whole lot of these weak classifiers, and each one "pushed" the final answer a little bit in the right direction, you'd have a strong, combined force for arriving at the correct solution. AdaBoost selects a set of weak classifiers to combine and assigns a weight to each.[21,22,23,] This weighted combination is the strong classifier.

Viola and Jones combined a series of AdaBoost classifiers as a filter chain, shown in Figure 3, that's especially efficient for classifying image regions. Each filter is a separate AdaBoost classifier with a fairly small number of weak classifiers.

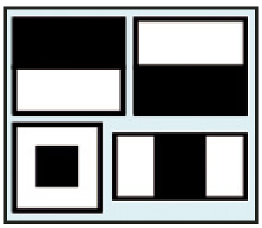

Figure 1. Examples of the Haar features used in OpenCV

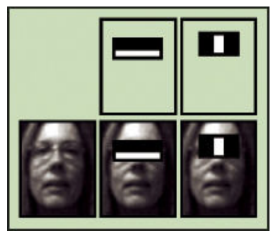

Figure 4. The first two Haar features in the original Viola-Jones cascade

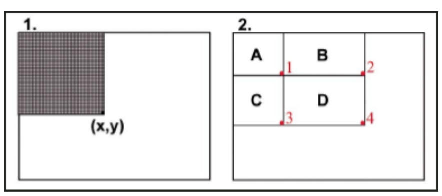

Figure 2. (Click for larger view.) The Integral Image trick.
***a*.After integrating, the pixel at (x,y) contains the sum of all pixel values in the shaded rectangle.**
***b*.The sum of pixel values in rectangle D is (x4, y4) - (x2, y2) - (x3, y3) + (x1, y1).**

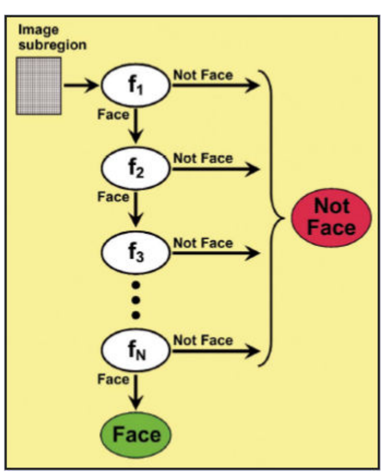

Figure 3. The classifier cascade is a chain of filters. Image subregions that make it through the entire cascade are classified as "Face." All others are classified as "Not Face."

The acceptance threshold at each level is set low enough to pass all, or nearly all, face examples in the training set. The filters at each level are trained to classifiy training images that passed all previous stages. During use, if any one of these filters fails to pass an image region, that region is immediately classified as "Not Face." When a filter passes an image region, it goes to the next filter in the chain. Image regions that pass through all filters in the chain are classified as "Face." Viola and Jones dubbed this filtering chain a cascade [26,27].

The order of filters in the cascade is based on the importance weighting that AdaBoost assigns. The more heavily weighted filters come first, to eliminate non-face image regions as quickly as possible. Figure 4 shows the first two features from the original Viola-Jones cascade superimposed on my face. The first one keys off the cheek area being lighter than the eye region. The second uses the fact that the bridge of the nose is lighter than the eyes.

A. Why Face Recognition?

The are many ways that humans can identify each other, and so is for machines. There are many different identification technologies available, many of which have been in commercial use for years. The most common person verification and identification methods today are Password/PIN known as Personal Identification Number, systems. The problem with that or other similar techniques is that they are not unique, and is possible for somebody to forget loose or even have it stolen for somebody else. In order to overcome these problems there has developed considerable interest in "biometrics" identification systems, which use pattern recognition techniques to identify people using their characteristics. Some of those methods are fingerprints and retina and iris recognition. Though these techniques are not easy to use. For example in bank transactions and entry into secure areas, such technologies have the disadvantage that they are intrusive both physically and socially. The user must position the body relative to the sensor, and then pause for a second to declare himself or herself. That doesn't mean that face recognition doesn't[3] need specific positioning. As we are going to analyse later on the poses and the appearance of the image taken is very important.

B. Skin Detection

Skin colour distribution has been shown to have its unique characteristics. There have been a number of face detection techniques that are based on the detection of skin colours, e.g, [8]. In this work, we have developed a SVM based method to detection skin. In this scheme, we divide the image into overlapping 4 x 4 blocks and process one block at a time, each time determining whether the center 2 x 2 pixels of the block are skin pixels. From the 4 x 4 colour block, we derive a 14 dimensional vector representing the colour and texture properties of the block. This 14-d vector is then presented to a SVM which are trained to make a binary decision, i.e., the center 2 x 2 pixels of the block belong to skin/non-skin.

III. STRATEGY USED IN FACE RECOGNTION

Image windows of various predefined sizes are moved across the image [28,29]. When a window is moved to a new position, a decision is made whether a face is contained inside the window. It is not difficult to see that such a scheme will be computationally very expensive because it has to search all locations of the image for all possible window sizes. In order to reduce the search effort, in this work, we first perform skin detection using a support vector machine based approach. Then face search will be only performed in those areas that contain skin colour[30,31,32]. Using such a scheme, we can increase the detection speed dramatically.

IV. CONCLUSION

We accomplished this by analyzing image sequences of facial expressions and then probabilistically haracterizing the facial muscle activation associatedwith each expression. This is achieved using a detailed physics-based dynamic model of the skin and muscles coupled with optimal estimates of optical flow in afeedback controlled framework.

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