Real Time Face Detection

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Abstract: Computer vision is a field of informatics, which teaches computers to see. It is a way computers gather and interpret visual information from the surrounding environment .The feature invariant approaches are used for feature detection of eyes, mouth, ears, nose, etc. In recent years, face recognition has attracted much attention and its research has rapidly expanded by not only engineers but also neuroscientists, since it has many potential applications in computer vision communication and automatic access control system.

Especially, face detection is an important part of face recognition as the first step of automatic face recognition. However, face detection is not straightforward because it has lots of variations of image appearance, such as pose variation like front, non-front, occlusion, image orientation, illuminating condition and facial expression. For example, the template-matching methods are used for face localization and detection by computing the correlation of an input image to a standard face pattern. The feature invariant approaches are used for feature detection of eyes, mouth, ears, nose, etc. This project presents a face detection technique mainly based on the color segmentation, image segmentation and template matching methods. The implementation is on Haar-casacde algorithm in order to detect the face from the given image dataset loaded by the user.

1. INTRODUCTION

This paper brings together new algorithms and insights to construct a framework for robust and extremely rapid visual detection. Toward this end we have constructed a frontal face detection system which achieves detection and false positive rates which are equivalent to the best published results (Sung and Poggio, 1998; Rowley et al., 1998; Osuna et al., 1997a; Schneiderman and Kanade, 2000; Roth et al., 2000). This face detection system is most clearly distinguished from previous approaches in its ability to detect faces extremely rapidly. Operating on 384 by 288 pixel images, faces are detected at 15 frames per second on a conventional 700 MHz Intel Pentium III. In other face detection systems, auxiliary information, such as image differences in video sequences, or pixel color in color images, have been used to achieve high frame rates. Our system achieves high frame rates working only with the information present in a single grey scale image. These alternative sources of information can also be integrated with our system to achieve even higher frame rates. There are three main contributions of our face detection framework. We will introduce each of these ideas briefly below and then describe them in detail in subsequent sections. The first contribution of this paper is a new image representation called an integral image that allows for very fast feature evaluation. Motivated in part by the work of Papageorgiou et al. (1998) our detection system does not work directly with image intensities.

Features:

Our face detection procedure classifies images based on the value of simple features. There are many motivations for using features rather than the pixels directly. The most common reason is that features can act to encode ad-hoc domain knowledge that is difficult to learn using a finite quantity of training data. For this system there is also a second critical motivation for features: the feature-based system operates much faster than a pixel-based system. The simple features used are reminiscent of Haar basis functions which have been used by Papageorgiou et al. (1998). More specifically, we use three kinds of features. The value of a two-rectangle feature is the difference between the sum of the pixels within two rectangular regions. The regions have the same size and shape and are horizontally or vertically adjacent (see Fig. 1). A three-rectangle feature computes the sum within two outside rectangles subtracted from the sum in a center rectangle. Finally a four-rectangle feature computes the difference between diagonal pairs of rectangles. Given that the base resolution of the detector is 24 × 24, the exhaustive set of rectangle features is

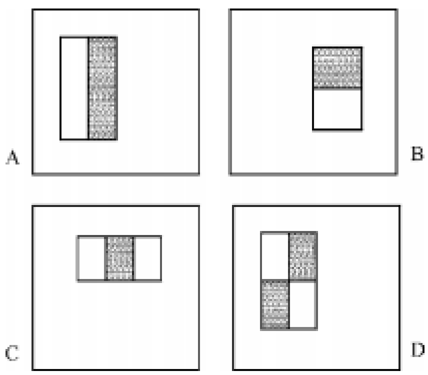
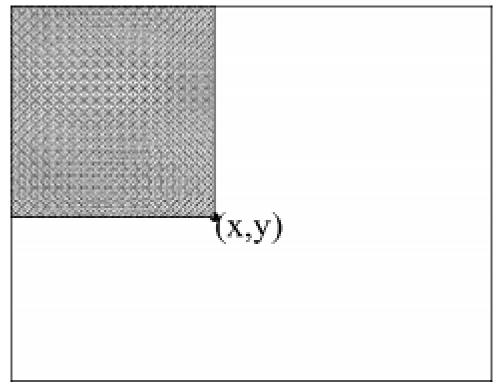


Figure 1. Example rectangle features shown relative to the enclosing detection window. The sum of the pixels which lie within the white rectangles are subtracted from the sum of pixels in the grey rectangles. Two-rectangle features are shown in (A) and (B). Figure (C) shows a three-rectangle feature, and (D) a four-rectangle feature. quite large, 160,000. Note that unlike the Haar basis, the set of rectangle features is overcomplete.3 2.1. Integral Image Rectangle features can be computed very rapidly using an intermediate representation for the image which we call the integral image.4 The integral image at location x, y contains the sum of the pixels above and to the left of x, y, inclusive: $ii(x, y) = \sum_{x' \leq x, y' \leq y} i(x', y')$, where ii(x, y) is the integral image and i(x, y) is the original image (see Fig. 2). Using the following pair of recurrences: $s(x, y) = s(x, y - 1) + i(x, y)$ (1) $ii(x, y) = ii(x - 1, y) + s(x, y)$ (2) (where s(x, y) is the cumulative row sum, $s(x, -1) = 0$, and $ii(-1, y) = 0$) the integral image can be computed in one pass over the original image. Using the integral image any rectangular sum can be computed in four array references (see Fig. 3). Clearly the difference between two rectangular sums can be computed in eight references. Since the two-rectangle features defined above involve adjacent rectangular sums they can be computed in six array references, eight in the case of the three-rectangle features, and nine for four-rectangle features. One alternative motivation for the integral image comes from the "boxlets" work of Simard et



al.

Figure 2. The value of the integral image at point (x, y) is the sum of all the pixels above and to the left.

2. OVERVIEW OF THE SYSTEM

Existing System:

Existing System is on using the "The Local Binary Pattern" operator (LBP) and HOG cascade classifiers to detect the face rectangular region in specific front_face rectangular region. Basically in LBP, For LBP, a binary pattern is extracted inside a given rectangular region. In this paper, we simplify the computational complexity of both HOG and LBP features for fast feature extraction time. To achieve this, we quantize the gradient angle into 2 orientations(horizontal and vertical axes).The LBP front_face xml files have many training data in order to locate the rectangular portion of the face in particular.

Disadvantages:

- LBP and HOG is less accurate when compared to the Haar Cascade Classifier which is implemented in the project.

• In any window inside an image, a huge amount of MB-LBP features can be found. So, during the training age, it is necessary to focus on a small set of critical features, discarding most of the non-critical ones in order to increase classification speed significantly without affecting accuracy.

Proposed System:

A more sophisticated method is therefore required. One such method would be the detection of objects from images using features or specific structures of the object in question. However, there was a problem. Working with only image intensities, meaning the RGB pixel values in every single pixel in the image, made feature calculation rather computationally expensive and therefore slow on most platforms .This problem was addressed by the so-called Haar like features, which is a trained cascade Due to its efficiency, Haar-like rectangle features have become a popular choice as image features in the context off detection. We compare our rectangular features with Haar like features Haar-like features are attributes extracted from images used in pattern recognition. Their name comes from their similarity to Haar wavelets. The utilization of these features instead of handling gray or color level of the pixels directly was proposed in. First, the pixel values inside the black area are added together; then the values in the white area are summed, then the total value of the white area is subtracted from the total value of the black area. This result is used to categorize image sub-regions.
The image that is passed to detect the face using the haar cascade classifier plots the rectangular region in most accurate manner.

Advantages:

• As occurs in LBP cascades, weak classifiers become strong classifiers when arranged in sequence in Haarlike cascade.
• We select the features with minimum error rate, which means they are the features that best classifies the face and non-face images.
• The accuracy rate also is more using the haar cascade classifier in order to detect the faces in specific front faces rectangular region.

3. SYSTEM DESIGN

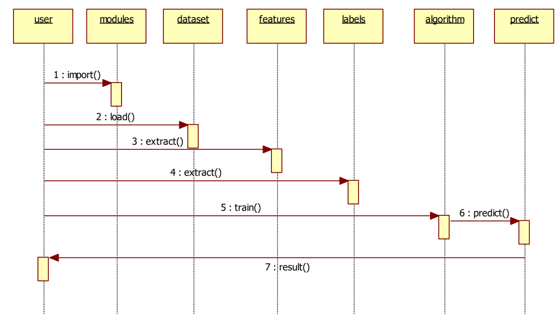


Fig 3.1: Sequence Diagram

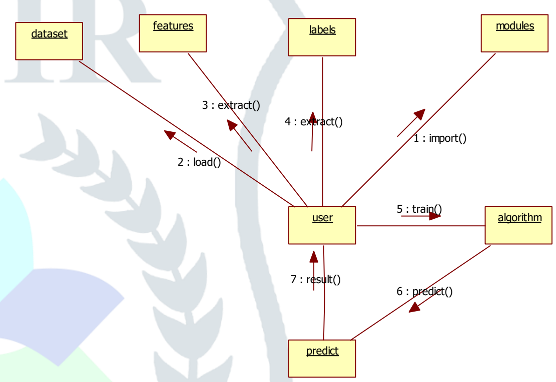


Fig 3.2: Collaboration Diagram

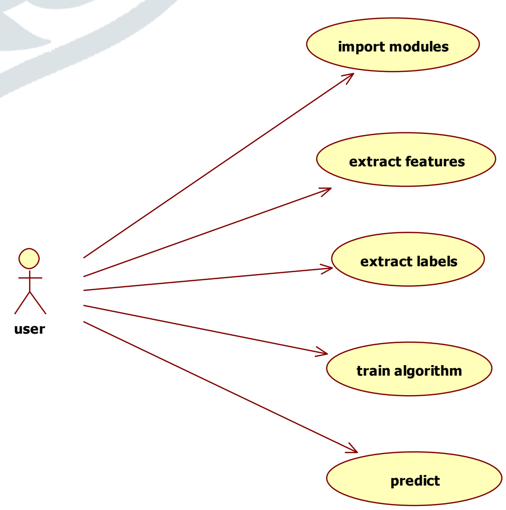


Fig 3.2: SYSTEM USE CASE DIAGRAM

4. OUTPUT SCREEN SHOTS

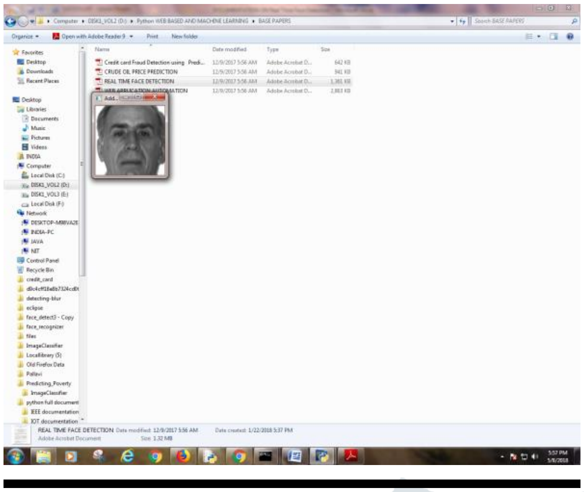


Fig 4.1 Face Detection

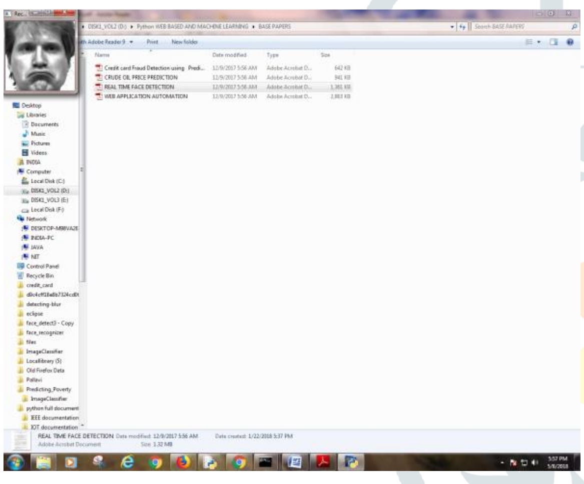


Fig 4.2: Face Detection

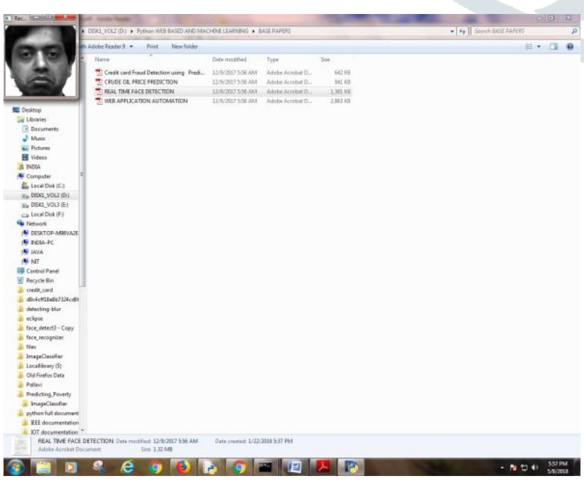


Fig 4.3: Face Detection

5. CONCLUSION

Raspberry Pi development board is a cost effective fully functional computational system can be used for many applications. PIR motion sensor and camera modules are also cost effective and can be used for surveillance systems. Using Python and OpenCV in Raspberry Pi, made our project flexible and adoptable to any required future changes.

6. REFERENCES

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