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AN EFFICIENT IMPLEMENTATION OF FPGA BASED FACE DETECTION AND FACE RECOGNITION SYSTEM USING HAAR CLASSIFIERS.

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ABSTRACT

This paper introduces a novel technique to detect faces similarly recognizes in real-time with very high rate. It is essentially a feature-based approach, in which a classifier is trained for Haar-like rectangular features selected by AdaBoost algorithm and efficient representation method histogram equalization is used for varying illumination in the image. The face detection system generates an integral image window to perform a Haar feature classification during one clock cycle. And then it performs classification operations in parallel using Haar classifiers to detect a face in the image sequence. The classifiers in the beginning of the cascade are simpler and consist of smaller numbers of features. Although a face detection module is typically designed to deal with single images, its performance can be further improved if video stream is available. However, as one proceeds in the cascade, the classifiers become more complex. A region is reported as detection only if it passes all the classifier stages in the cascade. If it is rejected at any stage, it is discarded and not processed further. If all stages are passed the face of a candidate is concluded to be recognized face.

Key Words - Ad boost algorithm, haar features, histogram equalization, integral image.

I. INTRODUCTION

Computer vision is one of the foremost fields which have experienced increasing number of applications in the recent years in various directional domains like biomedical imaging, surveillance systems, interactive systems like gesture, recognition, gaming etc. Detection of human faces is one of the key elements in the applications of computer vision in the above mentioned domains. Face detection is based on identifying and locating a human face in image regardless of size, position, and condition. Numerous approaches have been proposed for face detection in images. Simple features such as color, motion, and texture are used for the face detection in early researches. However, these methods break down easily because of the complexity of the real world. Face detection proposed by Viola and Jones [1] is most popular among the face detection approaches based on statistic methods. This face detection is a variant ofthe AdaBoost algorithm [2] which achievesrapid and robust face detection. The proposedface detection framework based on theAdaBoost learning algorithm using Haarfeatures with varying illumination isconsidered one of the most difficult tasks forface detection. Variation caused byillumination is highly non linear and makestask extremely complex. Well known one is contrast enhancement algorithm, histogram equalization is applied for compensating the illumination conditions. Over past two decades, the problem of face detection has attracted substantial attention and witnessed an impressive growth in basic and applied research, product development and application. The purpose of this paper is to implement and thereby recreate the face detection algorithm presented by Viola-Jones with a refinement of histogram equalization technique. This algorithm should be capable of functioning in an unconstrained environment meaning that it should detect all visible faces in any conceivable image. In order to guarantee optimum performance of the developed algorithm the vast majority of images used for training, evaluation and testing are either found on the internet or taken from private collections, which have been tested.

A. Overview

Facial feature detection methods generally model two types of information. The first is local texture around a given feature, for example the pixel values in a small region around an eye. The second is the geometric configuration of a given set of facial features, e.g. eyes, nose, mouth etc. This paper encloses four 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 comprising, will discuss the various composition required for face detection: integral image, haar features, ad boost algorithm and histogram equalization. Section 3 will specifically discuss the proposed hardware architecture. Section 4 deals with the implementation and experimental results.

COMPOSITION REQUIRED FOR FACE DETECTION

A. Integral Image

Integral images can be defined as two-dimensionallookup tables in the form of a size of the original image .This allows to compute sum of rectangular areas in the image, at any positioner scale, using only four lookups,

Sum=pt4 - pt3 - pt2+ ptl(1) where points p1" belong to the integral image. The new image representation called integral

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image paves way for fast feature

evaluation [3]. The integral image at location (x, y) contains the sum of the pixels above and to left of (x, y), as shown in figure 1.

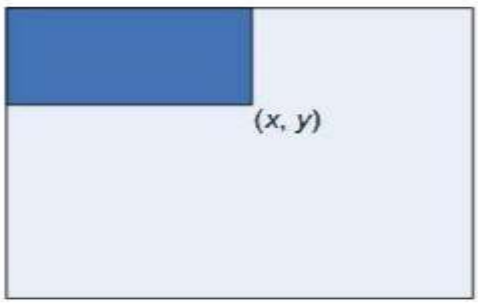

Figure 1. The shaded region represents the sum of pixels up to the position (x, y) of the image.

The shaded region represents the sum of pixels up to the position (x, y) of the image. Using the integral image anyrectangular sum can be computed in four array references [4], figure 2 illustrates the integral image sum generation, the sum of the pixels within rectangle D can be computed with four array references. The value of the integral image at location 1 is the sum of the pixels in rectangle A. The value at location 2 is A + B, at location 3 is A + C, and at location 4 is A + B + C +D. The sum within D can be computed as 4 + 1 - (2+ 3).

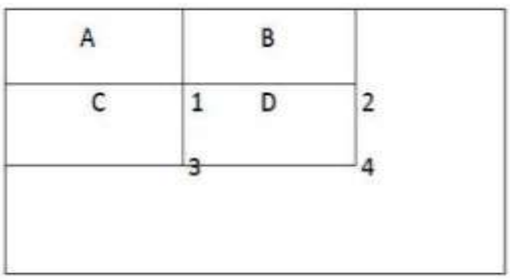

Figure2. Rectangular sum computation.

B. Haar Features

Haar-like features are digital image features used in face detection. They owe their name to their intuitive similarity with Haar wavelets and were used in the first real-time face detector [5]. A Haar-like feature considers adjacent rectangular regions at a specific location in a detection window as indicated in figure 3, it sums up the pixel intensities in these regions and calculates the difference between them. This difference is then used to categorize subsections of an image. For example, let us say we have an image database with human faces. It is a common observation that among all faces the region ofthe eyes is darker than the region of the cheeks. Therefore a common haar feature for face detection is a set of two adjacent rectangles that lie above the eye and the cheekregion. The position of these rectangles are defined relative to a detection window that acts like a bounding box to the target object (the face in this case).

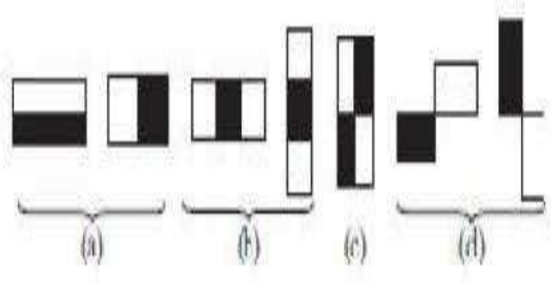

Figure 3. Examples of haar features.

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C.Haar Features Calculation

Haar features are composed of either two or three rectangles. Face candidates are scanned and searched for Haar features of the current stage. The weight and size of each feature and the features themselves are generated using a machine learning algorithm from AdaBoost [6]. Each Haar feature has a value that is calculated by taking the area of each rectangle, multiplying each by their respective weights, and then summing the results. Several Haar feature compose a stage. A stage comparator sums the entire Haar feature resulting in a stage and compares this summation with a stage threshold. The threshold is a constant obtained from the AdaBoost algorithm [7].The face detection algorithm eliminates face candidates quickly using a cascade of stages. The cascade eliminates candidates by making stricter requirements in each stage with later stages being much more difficult for a candidate to pass. Candidates exit the cascade if they pass all stages or fail any stage. A face is detected if a candidate passes all stages. This process isshown in Figure 4. Candidate must pass

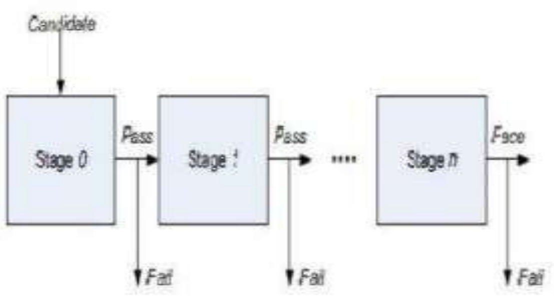

Figure 4. Cascade of stages.

all stages in the cascade to be concluded as a face.

D. Adaboost Algorithm

AdaBoost, short for Adaptive Boosting, is a machine learning algorithm, formulated by Yoav Freund and Robert Schapire [8].The adaboost algorithm is based on the idea that a strong classifier can be created by linearly combining a number of weak classifiers. A weak classifier consists of a feature (j), a thresh hold (θ), and a polarity (P)indicates the direction of the inequality:

$$h(x,f,p,\theta) = \begin{cases} 1 \ if \ pf(x) < p\theta \\ 0 \ otherwise \end{cases} \quad (2)$$

In the boosting algorithm T hypotheses are constructed each using a single feature. The final hypothesis is a weighted linear combination of the Thypotheses where the weights are inversely proportional to the training errors. Each iteration t, itwill train a best weak classifier which can minimizes the training errors. After T iteration, we can obtain a strong classifier which is the linear combination of the T best weak classifiers multiplied by the weight values. The AdaBoost algorithm is used to select a set of features and train a classifier. Locating such features is an important stage in many facialimage Interpretation tasks (such as face verification, face tracking or face expression recognition). We adopt the fast and efficient face finder recently described by Viola and

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Jones to locate the approximate position of each face in an image. A detector is used to cascade the structure to reduce the number of features considered for each sub-window. We then use the same method, trained on regions around facial feature points, to locate interior points on the face. However, there is often insufficient local structure around each feature to train really reliable feature finders. We find that when set with thresholds sufficient to locate the true position of the face.

E. Histogram Equalization

Often images may be limited to colors that is, it may be extremely grey, it lacks detail since the range of colors seems limited to mid grey levels or lacking in contrast enhancement. This enhancement is done with histogram equalization, as shown in figure 5(a)and 5(b), to expand the colors within the image. Todo this, we need to calculate the cumulative frequencies within the image. The cumulative frequency for grey level g is defined as the sum of the histogram data 0 to g [9]. If the cumulative frequency is stored in an array, histogram equalization can be written as:

alpha = 255 / number of Pixels (3)

g(x,y)=cumulative frequency[f(x,y)]* alpha (4)

g(x, y) is the grey level of pixel (x, y),
f(x, y) is the cumulative frequency.

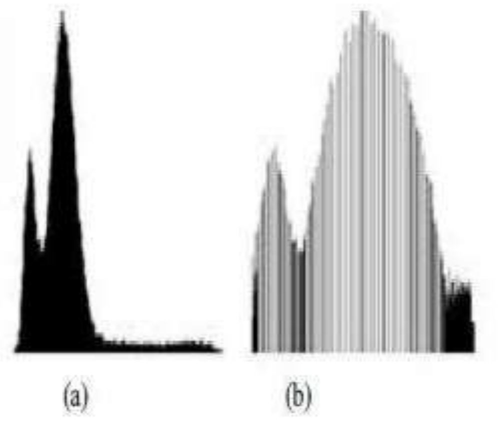

Figure 5. (a) An image histogram, (b) The result of (a) after histogram equalization.

PROPOSED FACE DETECTION.

The entire paper can be split up into two parts

A. Training,

B. Recognition.

A. Training

In the training phase the algorithm used is Adaboost. In this phase the image is split up into the sub image of size 19x 19. Thesub image is compared with the variables in the database obtained from the Yale [10]. The data base will have 2429 face variables and 4547 non face variables. Based on the later results the weights and based classifiers are updated. Then the sub image is processed to calculate the best threshold. The best threshold is calculated based on the previously trained data, which in tum depends on the haar feature classification. The Haar feature classifier ,classifies the face with non face based on five predetermined

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classifier values. These classifiers are identified as rectangle with four coordinates by calculating the integral image of the sub image. The integral image is nothing but the cumulative sum of all the image pixels. The process is repeated for the entire image with the sub image size as window. When the calculated threshold is found as weak classifiers it is then passed through the ad boost algorithm. The adaboost algorithm acts on the weak classifiers using alpha parameter and update the weight based onthat.

B. Recognition

Then the recognition algorithm is used to identify the data using the weights obtained from the training phase. The phase starts with sorting the weights with descending order. Then the image is normalized to identify the face and non face areas with the sorted weights. The image is splited with the sub image ofsize of 19x 19. The Haar cascade feature identification concept is used to identify the face and non face. The Haar cascade feature works on the basis of Haar feature calculation. This process repeated for the entire image to identify the face region.

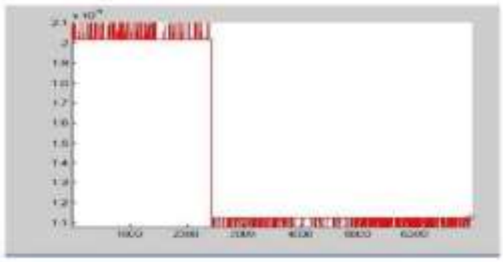
IV IMPLEMENTATION AND EXPERIMENTAL RESULT

A. Implementation

The implementation uses the database which consists of 2429 face images and 4547 non face images. Training with yale database took 50 hours approximately and the algorithm accuracy is found as 93%.In our case we use image of variable sizes and with minimum rectangle of size 19x 19 to obtain best feature extraction. The implementation consists of feature rectangle associated with the haar features. For every image we have calculated 51000 haar features using above said rectangle. We used the 14x 18 matrix classifier ranging from 0 to 6183 and used 6976 weights ranging from 0.000095 to 0.00023 which is distributed with range of 200% to recognize the face in the image.

B. Experimental Result

The elapsed time taken for recognition of lens image is 19.620610 seconds. The figure illustrates the distribution of weights after training.



The face detected output images are shown in figure.7.

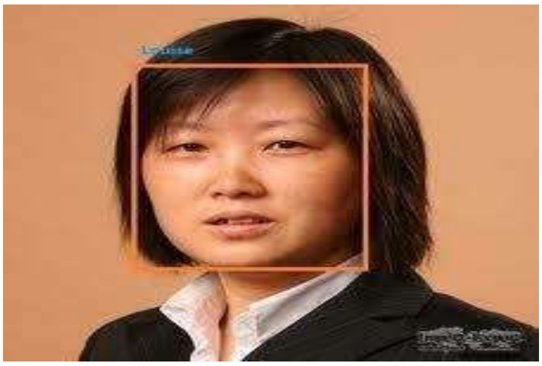


Figure 7 .Face recognized output.

V. CONCLUSION

In this paper the FPGA module can detect faces with reliability in real time. This paper has verified a process that overcomes low detection rates caused by variation in illumination using histogramequalization. The proposed face detection developed with adaboost algorithm can detect faces with high reliability.

VI. FUTURE EXTENSION

Various face recognition techniques are represented through various classifications such as, Image-based face recognition and Video-based recognition, Appearance based and Model-based, 2D and 3D face recognition methods. This paper gives a review of different face recognition techniques available as of today. The focus is on subspace techniques, investigating the use of image pre-processing applied as a preliminary step in order to reduce error rates. The Principle Component Analysis, Linear Discriminant Analysis and their modified methods of face recognition are implemented under subspace techniques, computing False Acceptance Rates (FAR)and False Rejection Rates (FRR) on a standard test set of images that pose typical difficulties for recognition. By applying a range of image processing techniques it is demonstrated that the performance is highly dependent on the type of pre-processing steps used and that Equal Error Rates (EER) of the Eigenface and Fisherface methods can be reduced using the method.

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