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# HUMAN FACE RECOGNITION USING WEIGHTED Co-OCCURRENCE HISTOGRAM OF ORIENTED GRADIENTS (W-CoHOG)

**[1] Beesetty G P Hima Ketan, [2]ValliKumari Vatsavayi**
[1,2] Dept. of Computer Science and Systems Engineering, Andhra University, Visakhapatnam, India
[1] chinnihima1992@gmail.com

***Abstract*— Face Recognition is an essential task in many areas. A method of face recognition using Weighted Co-occurrence Histogram of Oriented Gradient (W-CoHOG) is presented in this paper. In the recent times, the approach of Co-occurrence Histogram of Oriented Gradient (CoHOG) is being applied widely in face recognition. In this paper, we are applying Weighted Co-occurrence Histogram Oriented Gradient (W-CoHOG). W-CoHOG is an extension of CoHOG and it takes magnitude also instead of only considering pair of orientations one where in Weighted Co-occurrence matrix is computed and histograms are calculated. W-CoHOG have recognition accuracy higher than CoHOG. In this paper, weighted co-occurrence histogram of oriented gradients (W-CoHOG) concept is introduced for computing also the magnitude to improve the accuracy. Magnitude value is included to influence the feature vector to achieve better performance than existing methods. Experiments were conducted on two face recognition datasets namely YALE and CALTECH. The experiment results support our approach.**

***Keywords*— Histograms of Oriented Gradients (HOG), Co-occurrence histogram of oriented gradients (CoHOG), Weighted Co-occurrence histogram of oriented gradients (W-CoHOG).**

## I. INTRODUCTION

Computer Vision is a wide and emerged area over the past few years. Face recognition is a big problem in computer vision. Many applications are based on face recognition such as Biometric systems, video surveillance, etc. The main goal of face recognition is to check the given human face with the person in our database. If the human face is identified in the particular image and then it can be used for further analysis. Face recognition is one of the challenging problems in Computer Vision, due to Continuous variations of facial appearance due to illumination, pose, expression, and occlusion. In this paper, human face in a static image is identified. Identifying human face in a static image is difficult than video sequence because of no motion and background information available to provide clues to approximate human face. In our approach, the input of the face recognition system is a human face image and output is a similar human face image present in our database if no similar face found then it will give us image not found a message. In this paper, static images are considered for face recognition.

## II. RELATED WORK

One of the biggest problems of face recognition is to find efficient methods for face representation. There are many such methods. In some face representation methods they use transformations and statistical methods to find the basic vectors to represent the face. Such methods are as PCA, LDA [5], ICA. Another method is a feature based approach. Basically, they are structural based approaches using geometric relationships among the facial features like mouth, eyes, and nose. A method in this category is SIFT, HOG. SIFT [13] has emerged as one of the most used detections/description schemes for its ability to handle image transformations like scale changes (zoom), image rotation, and illumination. The major steps of the SIFT algorithm are Scale-space extreme detection, Orientation assignment, Key point descriptor. Histogram based features are popularly used in Face recognition, human recognition, and object detection because of their robustness. Histogram of Oriented Gradients (HOG) is a famous and effective method for Face detection. It uses histograms of oriented gradients as a feature descriptor. HOG features are robust towards illumination variances and deformations in faces. In [7], HOG descriptors are extracted from regular grids and used for classification. To increase accuracy, the multiscale obtained by computing HOG of grids at different sizes is also considered. To combine classifiers at different grid sizes, the vectorization is used. CoHOG is an extension of HOG that considers the relation between pairs of oriented gradients. Co-HOG have been successfully applied in face recognition problem [8]. In that work, they use CoHOG to represent faces in face recognition. Recently Weighted Co-occurrence histogram oriented gradients (W-CoHOG) [2] has been used for Feature Extraction in Human Detection. In our work, we use W-CoHOG for face recognition where gradient magnitude also has a contribution in W-CoHOG computation. The remainder of this paper is organized as follows; section 3 gives a brief overview of HOG, CoHOG. Proposed method W-CoHOG is discussed in section 4 in detail. Section 5 contains experimental results and comparison with existing methods. Finally, the work concluded in section 6.

## III. BACKGROUND

### A. HOG

A HOG descriptor is a histogram which counts gradient orientation of pixels in a given image I. In particular, first, the gradient image I is computed as I = {Gmag, Gdir}, Gmag and Gdir being respectively magnitude and orientation of gradient. Secondly, the image is divided into n non-overlapping regions. Then histograms of oriented gradients are calculated for each and every small region. Finally, histograms of each region are concatenated using vectorization.

B. CoHOG

Co-occurrence histograms of oriented gradients (CoHOG) is an extension to HOG and more robust than HOG. In this section, CoHOG is explained. It considers the relation between pairs of pixels. CoHOG use a two-dimensional histogram whose bin is a pair of edge gradient direction between the interest pixel and the offset pixel. Co-occurrence matrix calculated for the pair of gradient orientation with different offsets.

$$C_{\Delta x,\Delta y}(p,q) = \sum_{i=1}^{n}\sum_{j=1}^{m} \begin{cases} 1, if I(i,j) = p \; and \; I(i+x, j+y) = q \\ None Otherwise \end{cases}$$

(1)

Equation (1) shows the calculation of Co-occurrence matrix.

Let I is a given input image. Where p, q are any two orientations in given eight orientations and is offset for co-occurrence and m, n are a number of rows and columns of a matrix. is co-occurrence matrix for a given offset and orientation p, q.

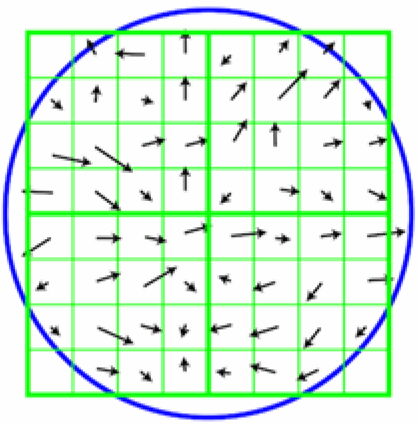

Fig.1. Image Gradients

## IV. PROPOSED METHOD (W-CoHOG)

A. Overview

In the proposed method magnitude is also considered to extract more robust feature. W-CoHOG concept is proposed for better feature description. Figure (1) briefly explains the process of W-CoHOG method.


Initially, gradients of an image are computed in magnitude and direction form and converted into oriented gradients. Next, the image is divided into 3x6 or 6x12 non-overlapping cells. Then, weighted co-occurrence matrices computed for each region. After that, all weighted co-occurrence matrices of all regions are combined.

B. FEATURE EXTRACTION

This section presents a novel feature descriptor with W-CoHOG to obtain expression and pose invariance. The first step of calculation in many feature detectors in image pre-processing is to ensure normalized color and computation of the gradient values. For a given input image gradients are computed for each pixel. In this method, Sobel and Robert's filters are used to compute gradients of a given input image. Equation (2), (3) shows gradient calculation using Sobel and Robert's filters respectively for a given input image I, is as shown in below.

Sobel Gradient Operator

$$\textbf{(a)}\; G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * I$$

$$\textbf{(b)}\; G_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * I \qquad (2)$$

Robert's Gradient Operator

$$\textbf{(a)}\; G_x = \begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} * I$$

$$\textbf{(b)}\; G_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix} * I \qquad (3)$$

Then, gradients are converted into magnitude and direction using equation (4). The gradients directions are converted into eight equal bins with 450 intervals.

$$\textbf{(a)}\; \theta = \tan^{-1}\frac{g_x}{g_y} \qquad \textbf{(b)}\; m = \sqrt{{g_x}^2 + {g_y}^2}$$

(4)

After that, magnitude matrix is convoluted with a mean mask to eliminate noise which may cause an aliasing effect. Eq (5) shows the 12 X 12 mean mask used in the proposed method.

$$Conv_{12 \, x \, 12} = \frac{1}{144}\begin{bmatrix} 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \\ 1 & 1 & 11 & 1 & 11 & 1 & 11 & 1 & 1 \end{bmatrix} \qquad (5)$$

C. W-CoHOG:

In this proposed method magnitude component of a gradient used as weight function to calculate weighted co-occurrence matrix. In order to calculate magnitude weighted co-occurrence matrix the magnitude weights of each pixel are calculated. The Weight function is applied to co-occurrence matrix to influence the co-occurrence matrix using the gradient magnitude of each pixel. The weight functions used in this method are described in the following paragraph.

Let I is a given input image. *i, j* are any two orientations in given eight orientations and Δ*x,* Δy is offset for $C_{\Delta x, \Delta y}(i,j)$ is weighted co-occurrence matrix for a given offset Δ*x, Δy*, and orientation *i,j*. The Eq. 6 and 7 describes the calculation of the weighted co-occurrence matrix.

$$C_{\Delta x \Delta y}(i,j) = \sum_{p=1}^{n} \sum_{q=1}^{m} \{ W_{(p,q),(p+\Delta x, p+\Delta y)} * \alpha \quad (1)$$

Where

$$\alpha = \begin{cases} 1 & if O(p,q) = i and O(p+\Delta x, q+\Delta y) = j \\ 0 & Otherwise \end{cases}$$

Let $m_{p,q}$ is a gradient at a given pixel p,*q* for a given input image *I*. $\bar{M}$ and $M_{max}$ are mean and maximum gradient values in *I*. The weight calculation was performed with simple operations like mean and division operations. Eq.8 and 9 show two possible weight function to calculate the weight for a given pixel *(p,q)*and *(p+*Δ*x, q+Δy).A*ny of two functions is preferable to calculate weights for calculating weighted co-occurrence matrix. In this proposed method, Eq (8) is used to calculate weights for experimental results.

$$W_{(p,q),(p+\Delta x, p+\Delta y)} = \left(\frac{m_{p,q}}{\bar{M}} * \frac{m_{p+\Delta x, p+\Delta y}}{\bar{M}}\right) + \mu \quad (2)$$

$$W_{(p,q),(p+\Delta x, p+\Delta y)} = \left(\frac{m_{p,q}}{M_{max}} * \frac{m_{p+\Delta x, p+\Delta y}}{M_{max}}\right) + \mu \quad (3)$$

(4)

Where, μ is constant and μ=1.After computing magnitude weighted co-occurrence matrices for all regions, the matrices are vectorized by simple concatenation of all matrix rows into a single row. Our proposal will improve the performance of face recognition system with W-CoHOG feature extraction. In this system, we are applying magnitude also to improve the recognition rate. Including magnitude will influence the feature vector to achieve better performance than existing method. Initially gradients of an image are computed in direction form and convert it into oriented gradients. Then we will extract features of images using W-CoHOG. It calculates the W-CoHOG to the given individual from test data and compares to the all other individuals W-CoHOG value in the database and displays the matched image or gives a message as 'Image not found.

*Algorithm 1***:** Feature Extraction with W-CoHOG Calculation

**Given Image**: I
**Given offset:** x,y
**Begin**
Calculate O,M of I
Divide image into cells
**For each** cell in the image
**Initialize** co-occurrence matrix C←0
**For each** pair of orientation (i,j)
**For each** pixel p,q in the cell
Calculate $W_{(p,q),(p+x,q+y)}$
**If** $O_{p,q}$ =i and $O_{p+x,q+y}$=j **then**
$C_{p,q}=C_{p,q}+1*W_{(p,q),(p+x,q+y)}$
**end**
**else**
$C_{p,q}=C_{p,q}+0*W_{(p,q),(p+x,q+y)}$
**end**
**end**
**end**
**end**
H←vectorizeall co-occurrence matrices
**return** H
**end**

## V. EXPERIMENTAL RESULTS

The proposed method is evaluated on two datasets: YALE and CALTECH datasets which contain 165 and 450 images. YALE contains total 165 images of 15 subjects and CALTECH contains total 450 images of 27 subjects. Images were taken in different facial expressions: happy, normal, sad, sleepy, surprised, different hairstyles, backgrounds, wink and lightening conditions with/without glasses. During experimentation, we created two databases such as training database and testing database for each dataset. The training data contain all the images of dataset and testing data contain some images by randomly picking images from YALE and CALTECH databases to evaluate the performance our system in varying conditions. Each image size in YALE dataset is 100 x 120 pixels and image size in CALTECH dataset is 100 x 66.

Fig.2.YALE sample images in dataset

Fig.3.CALTECH sample images in dataset

Figure 2 and 3 shows that sample example of YALE dataset and CALTECH datasets respectively. Simple sobel filter and Roberts filter were used to calculate the gradients of an input image.

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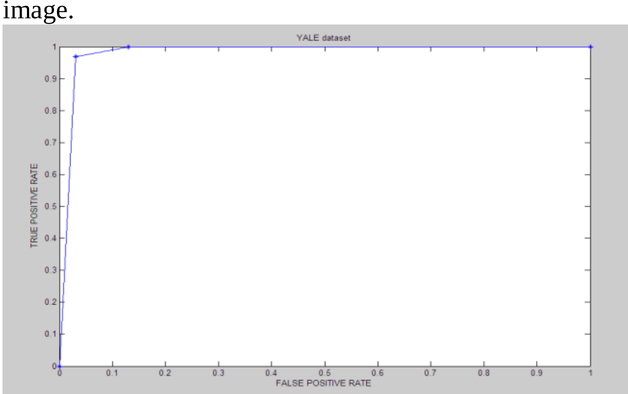


Fig.4. ROC curve on YALE Dataset

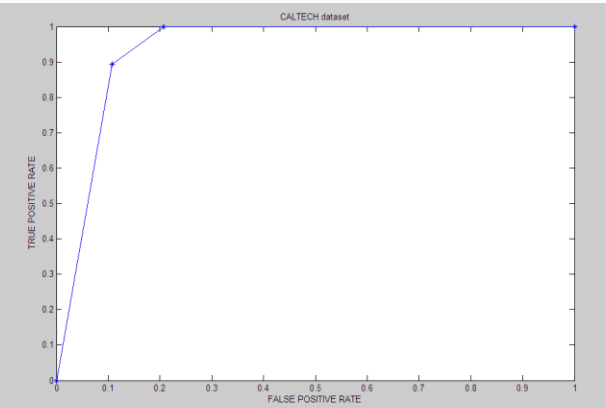


Fig.5. ROC curve on CALTECH Dataset

ROC curves are used for performance evaluation of binary classification like object detection problems. In this paper, True Positive rate Vs False Positive per Window (FPPW) were plotted to evaluate the performance of proposed method. A ROC curves towards the top-left of the graph means better performance for classification problem. The figure 4 and 5 clearly shows that curves obtained by proposed method achieved better recognition rate for all false positive rate than other existing methods or as at least comparable. The accuracy of the classifier also performed better that other state of art methods shown in the figure.

## CONCLUSIONS

In this paper, a new method called W-CoHOG is proposed which is an extension work to CoHOG. Magnitude is also added to feature vector to improve the accuracy of image retrieval. The proposed method achieved improvement in accuracy on two benchmark datasets. Experimental results prove that performance of the proposed method is better than another state of art methods. Even though calculation of weights adds additional computational complexity, the overall feature vector generation time decreased by reducing the number of offsets to two. Future work involves better feature extraction method for face recognition.

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