Discriminant Analysis of Haar Features for Accurate Eye Detection

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Abstract— *The efficient and discriminating feature extraction is a significant problem in pattern recognition and computer vision. This paper presents a novel Discriminating Haar (D-Haar) features for eye detection. The D-Haar feature extraction starts with a Principal Component Analysis (PCA) followed by a whitening transformation on the Haar feature space. A discriminant analysis is then performed on the reduced feature space. A set of basis vectors, based on the novel definition of the within-class and between-class scatter vectors and a new criterion vector, is defined through this analysis. The D-Haar features are derived in the subspace spanned by these basis vectors. We then present an accurate eye detection approach using the D-Haar features. Experiments on Face Recognition Grand Challenge (FRGC) show the promising discriminating power of D-Haar features and the improved detection performance over existing methods.*

Keywords: Haar Wavelet; Discriminant Analysis; Eye Detection; Face Recognition Grand Challenge

1. Introduction

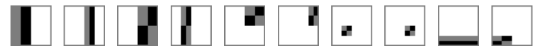
Previous research has proved that various image representations can provide more information for detection and recognition than pixel-by-pixel intensity values [1] [2] [3] [4]. Due to the state-of-the-art work of Viola and Jones [4], Haar wavelet representation attracts much attention in the past decade [5] [6] and it is widely used in image retrieval [7], pedestrian detection [4], as well as face detection and recognition [8]. The Haar wavelet is a set of basis functions which is capable of capturing the relationship between average intensities of neighboring regions in different scales and orientations. The main reasons of using Haar wavelet in our work are (i) its intensity difference encoding scheme is suitable to capture the structure characteristic of eyes: centered dark pupil is surrounded by a relatively white sclera and (ii) the inner product of Haar basis functions with an image vector can be efficiently performed by just several integer additions and subtractions instead of floating point multiplications [4].

One important problem of Haar wavelet feature is that it resides in an extremely high dimensional space. However, low dimensionality is especially important for learning, as the number of examples required for attaining a given level of performance grows exponentially with the dimensionality of the vector space [9]. A simple choice of dimensionality reduction is the Principal Component Analysis (PCA) [10]. PCA is probably the most widely used dimensionality reduction technique with the property of optimal data representation in the sense of minimum mean-square error. Although PCA can derive the optimal representing features, it can not derive the optimal discriminating features. However, in contrast to the case of pattern classification, where we need to decide between a relatively small number of classes, the detection problem requires us to differentiate between the object class and the rest of the world. As a result, the extracted features for object detection must have discriminating power to handle the cluttered scenes it will be presented with. Furthermore, in modeling complicated classes of objects like eyes, the inner-class variability itself is also significant. One widely used discriminating feature extraction method is the Fisher Linear Discriminant (FLD) [10]. For any L-class pattern classification problem, FLD derives a compact and well-separated feature space based on $L-1$ basis vectors that maximize the between-class distance while minimize the within-class distance. However, when applied to the two-class detection problem, FLD only derives one basis vector, which will lead to the significant loss of data information and a very poor classification performance. Another popular feature extraction method is Adaboost [4]. Adaboost is a performance guided greedy algorithm. On each round one sub-optimal discriminating feature which can generate the best performance is chosen and a weak classifier is built upon this feature. After several rounds, the final feature space is built by combining a set of these sub-optimal discriminating features and a strong classifier is built by combining a collection of weak classifiers. Adaboost has some disadvantages when applied to real applications. First, it can not deal with large-scale training set because of its great time and space requirement; second, in some cases, especially when the characteristic of training samples vary in a large range, the convergence of the training procedure can not be guaranteed; finally, the speed of both training and testing procedure is very slow, which can not meet the real-time requirement.

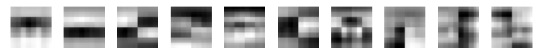
In this paper, we present a novel discriminating Haar (D-Haar) features, which reside in low dimensional space and have great discriminative power. The D-Haar feature extraction starts with a Principal Component Analysis (PCA) followed by a whitening transformation on the Haar feature space. A discriminant analysis is then performed on the reduced feature space. A set of basis vectors, based on the novel definition of the within-class and between-class scatter vectors and a new criterion vector, is defined through this analysis. The D-Haar features are derived in the subspace spanned by these basis vectors. Experiments will show the promising discriminating power of D-Haar features.

We then present an accurate eye detection approach using the D-Haar features. Eye detection has a significant impact on the performance of an automatic face recognition system due to the "Curse of Alignment" [11]. Even a slight detection error will dramatically reduce the face recognition accuracy [11] [12]. Although lots of eye detection methods have been proposed recently [11] - [13], most of them evaluate their methods according to a loose criterion based on the binocular distance. This kind of error can be more than ten pixels depending on the different size of images and thus lead to a poor face recognition performance. The eye detection method proposed in this paper can achieve more accurate detection performance over existing methods. In particular, experiments on Face Recognition Grand Challenge (FRGC) show that our method has an overall 91.37% accuracy, with the detected eyes within five pixels from the ground truth.

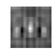
(a) Samples of Eye Images after Illumination Normalization



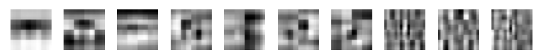
(b) Samples of Haar Basis Images (Haar Basis)



(c) First 10 Haar Basis Images after PCA (P-Haar Basis)



(d) The Only One Haar Basis Images after FLD (F-Haar Basis)



(e) First 10 D-Haar Basis Images

Fig. 1: Samples of eye images, Haar basis, P-Haar basis, F-Haar basis, and D-Haar basis.

2. Haar Wavelet Features

The Haar wavelet is a natural set basis functions which encode the differences in average intensities between different regions in different scales. It has three kinds of representations in two dimension space: (i) a two horizontal neighboring rectangular regions, which computes the difference between the sum of pixels within each of them, (ii) a two vertical neighboring rectangular regions, which computes the difference as (i) does, and (iii) a four neighboring rectangular regions, which computes the difference between diagonal pairs of rectangles. Figure 1(b) lists some examples of these Haar basis. Mathematically, the 2D Haar basis are given by a set of scaled and translated box like functions defined as follows:

$$f_{\omega,\mu,\nu}(x,y) = f_{\omega_1,\mu_1,\nu_1}(x) * f^t_{\omega_2,\mu_2,\nu_2}(y)$$

$$f_{\omega_1,\mu_1,\nu_1}(x) = \begin{cases} 1 & \mu_1 \le x \le \mu_1 + \nu_1/2 \\ -1 & \mu_1 + \nu_1/2 + 1 \le x \le \mu_1 + \nu_1 \\ 0 & \text{otherwise} \end{cases}$$

$$f_{\omega_2,\mu_2,\nu_2}(y) = \begin{cases} 1 & \mu_2 \le y \le \mu_2 + \nu_2/2 \\ -1 & \mu_2 + \nu_2/2 + 1 \le y \le \mu_2 + \nu_2 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $\omega = (\omega_1, \omega_2) \in \{1, 2, ..., S\}$, $\mu = (\mu_1, \mu_2) \in \{2^0, 2^1, ..., 2^{\omega-1}\}$, and $\nu = (\nu_1, \nu_2) \in \{0, 1, ..., 2^{\omega} - 1\}$ denote the scale, step, and shift of Haar wavelets in horizontal and vertical directions, respectively. Haar basis vector $\psi_{\omega,\mu,\nu}$ is then given by concatenating the columns of the box like function $f_{\omega,\mu,\nu}(x,y)$. Let $\Psi = \{\psi_{\omega,\mu,\nu} : \omega = (\omega_1, \omega_2) \in \{1, 2, ..., S\}, \mu = (\mu_1, \mu_2) \in \{2^0, 2^1, ..., 2^{\omega-1}\}, \nu = (\nu_1, \nu_2) \in \{0, 1, ..., 2^{\omega}-1\}\}$ denotes a set of basis vectors. A Haar feature space is constructed based on the set of basis vectors Ψ. Given an image column vector $X \in \mathbb{R}^{n_r \times n_c}$, where n_r and n_c denote the number of rows and columns of the image respectively. A Haar wavelet feature vector $\mathcal{Y}$ on image X is defined as follow:

$$\mathcal{Y} = \Psi^t X \tag{2}$$

The Haar feature vector is then normalized to zero mean and unit variance in case one feature excessively dominates the others. One advantage of Haar feature is that the inner product can performed by just several integer additions and subtractions instead of floating point multiplication [4].

Compared with some other state-of-the-art image representation methods such as Gabor [1], HoG [2] and LBP [3], Haar feature is considered the optimal representation for eye detection through our experiments, since its intensity difference encoding scheme is most suitable to capture the structure characteristic of eyes: centered dark pupil is surrounded by a relatively white sclera. A comprehensive assessment of Haar features with others can be found in our previous work [14].

3. Discriminating Haar Features

As we mentioned in Section 1, the extracted Haar features not only reside in a extremely high dimensional space but can not guarantee the discriminability property. We present in this section a novel discriminating Haar (D-Haar) features, which reside in low dimensional space and have great discriminative power. The D-Haar feature extraction starts with a Principal Component Analysis (PCA) followed by a whitening transformation on the Haar feature space. A discriminant analysis is then performed on the reduced feature space. A set of basis vectors, based on the novel definition of the within-class and between-class scatter vectors and a new criterion vector, is defined through this analysis. The D-Haar features are derived in the subspace spanned by these basis vectors.

Let the extracted Haar feature vector introduced in Section 2 be $\mathcal{Y} \in \mathbb{R}^N$, where N is the dimensionality of the Haar feature space. PCA is firstly performed to solve the high dimensionality problem. The covariance matrix is:

$$\sum_{\mathcal{Y}} = \varepsilon\{[\mathcal{Y} - \varepsilon(\mathcal{Y})][\mathcal{Y} - \varepsilon(\mathcal{Y})]^t\} \quad (3)$$

where $\varepsilon(\cdot)$ is the expectation operator and $\sum_{\mathcal{Y}} \in \mathbb{R}^{N\times N}$. The PCA of a random vector $\mathcal{Y}$ factorizes the covariance matrix $\sum_{\mathcal{Y}}$ into the following form:

$$\begin{aligned}\sum_{\mathcal{Y}} &= \Phi\Lambda\Phi \ with \ \Phi = [\phi_1\phi_2...\phi_N],\\ \Lambda &= diag\{\lambda_1, \lambda_2, ..., \lambda_N\}\end{aligned} \quad (4)$$

where $\Phi \in \mathbb{R}^{N\times N}$ is an orthogonal eigenvector matrix and $\Lambda \in \mathbb{R}^{N\times N}$ a diagonal eigenvalue matrix with diagonal elements in decreasing order ($\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_N$). Then, the PCA transformation is defined as follows:

$$R = P^t\mathcal{Y} \quad (5)$$

where $P = [\phi_1\phi_2...\phi_m]$, $m < N$, and $P \in \mathbb{R}^{N\times m}$. The first ten basis vectors that form the reduced Haar feature space after PCA is shown in Figure 1(c).

After PCA, the new feature vector R resides in a lower dimensional space ($\mathbb{R}^m$). In this $\mathbb{R}^m$ feature space, we then perform the whitening transformation to sphere the covariance matrix of R. The whitening transformation W is defined as follows:

$$W = \Gamma^{-1/2}P \quad (6)$$

where $\Gamma = diag(\lambda_1, \lambda_2, \cdots, \lambda_m)$. This whitening transformation not only eliminates the correlation between variables but also normalizes the deviation of each variable.

Next, we will define two scatter vectors and a criterion vector in order to derive the D-Haar features. Let $W = \{W_1, W_2, \cdots, W_m\}$, where $W \in \mathbb{R}^{N\times m}$. Note that W contains m vectors. The idea of the D-Haar transformation is to choose a smaller set of vectors, from these m vectors, with the most discriminating capability. The D-Haar transformation is then defined based on this smaller set of vectors. Toward that end, we first define the within-class scatter vector, $\alpha \in \mathbb{R}^m$, and the between-class scatter vector, $\beta \in \mathbb{R}^m$, as follows:

$$\alpha = P_1\sum_{i=1}^{n_1} s(W^ty_i^{(1)} - W^tM_1) + P_2\sum_{i=1}^{n_2} s(W^ty_i^{(2)} - W^tM_2) \quad (7)$$

and

$$\beta = P_1 s(W^tM_1 - W^tM) + P_2 s(W^tM_2 - W^tM) \quad (8)$$

where P_1 and P_2 are the prior probabilities, n_1 and n_2 are the number of samples, and $y_i^{(1)}$ and $y_i^{(2)}$ are the Haar features of the eye and the non-eye samples, respectively. M_1, M_2, and M are the means of the eye class, the non-eye class, and the grand mean in the original Haar feature space, respectively. The $s(\cdot)$ function defines the absolute value of the elements of the input vector. The significance of this new scatter vectors is that the within-class scatter vector, $\alpha \in \mathbb{R}^m$, measures the clustering capability of the vectors in W, and the between-class scatter vector, $\beta \in \mathbb{R}^m$, measures the separating capability of the vectors in W. In order to choose the most discriminating vectors from W to form a set of vectors to define the D-Haar transformation, we then define a new criterion vector $\gamma \in \mathbb{R}^m$, as follows:

$$\gamma = \beta./\alpha \quad (9)$$

where ./ is element-wise division. The value of the elements in γ indicates the discriminating power of their corresponding vectors in W: the larger the value is, the more discriminating power the corresponding vector in W possesses. Therefore, we choose the p vectors, $W_{i1}, W_{i2}, \cdots, W_{ip}$, in W corresponding to the p largest values in γ to form a transformation matrix $T = [W_{i1}, W_{i2}, \cdots, W_{ip}]$, where $T \in \mathbb{R}^{N\times p}$ and $p < m$. The D-Haar features are thus defined as follows:

$$\mathcal{Z} = T^t\mathcal{Y} \quad (10)$$

Recall that, in Eq. (2), we have that $\mathcal{Y} = \Psi^tX$. The D-Haar transformation is then defined as follows:

$$\mathcal{Z} = U^tX \quad (11)$$

where $U = \Psi T$, $U \in \mathbb{R}^{(n_r\times n_c)\times p}$, is the set of basis vectors that forms the D-Haar feature space. Figure 1(e) shows the first ten basis vectors of D-Haar features. The D-Haar features thus resides in the feature space $\mathbb{R}^p$ and capture the most discriminating Haar information of the original data X.

Note that our D-Haar Transformation is different from the commonly used discriminant analysis methods, such as Fisher Linear Discriminant (FLD) [10]. FLD seeks a set of basis vectors that maximizes the criterion $J = trace(S_w^{-1}S_b)$ [10], where S_w and S_b are the within-class and between-class scatter matrices. The criterion is maximized when the basis vectors are the eigenvectors of the

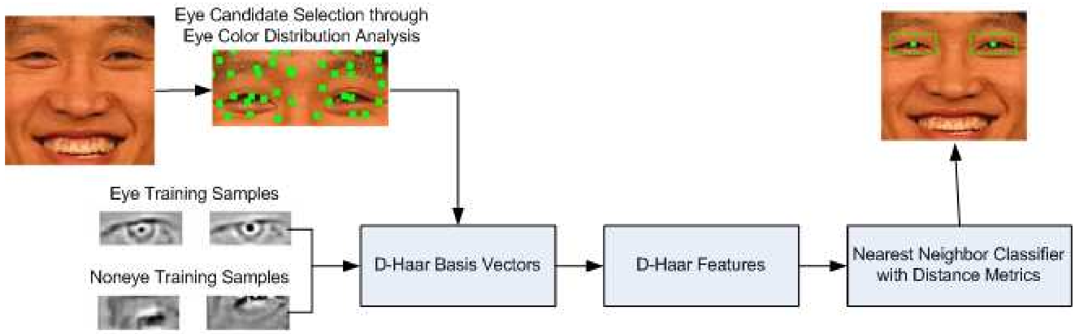


Fig. 2: System architecture of our eye detection method.

matrix $S_w^{-1}S_b$ corresponding to its largest eigenvalues. FLD can find up to $L-1$ basis vectors for the L-class pattern recognition problem. For a two-class eye detection problem, FLD is just able to derive only one feature, while our D-Haar transformation is able to derive multiple features for achieving more reliable eye detection results. The single discriminating Haar feature derived from FLD is showed in Figure 1(d).

4. Overview of Our Eye Detection Method

In this section, we present an accurate eye detection method using D-Haar features. Figure 2 illustrates the architecture of the method. First, a face is detected using the Bayesian Discriminating Features method (BDF) in [15] and normalized to the size of 128×128. Then Geometric constraints are applied to localize the eyes, which means eyes are only searched in the top half (within the size of 55×128 in our experiment) of the detected face. The effect of illumination variations are alleviated by applying an illumination normalization procedure combining of the Gamma Correction, Difference of Gaussian (DoG) filtering, and Contrast Equalization (Figure 1(a)). Then the eye detection is achieved by two steps: the feature based eye candidate selection and appearance based validation. The selection stage chooses eye candidates through an eye color distribution analysis in the YCbCr color space based on the observation that the pixels in the eye region, compared with other skin area, have higher chrominance blue (Cb) value, lower chrominance red (Cr) value, and lower luminance (Y) value [14]. 99% pixels of an image are rejected in this stage and only remaining 1% pixels are further processed by the validation stage. The validation stage first extracts the D-Haar features of each candidate and then a nearest neighbor classifier with different distance metrics is applied for classification to detect the center of the eye among these candidates. Usually, there are multiple eyes detected around the pupil center. The final eye location is the average of these multiple detections.

5. Experiments

In this section, we evaluate the performance of D-Haar features and the proposed eye detection method. The experiments are performed using the Face Recognition Grand Challenge (FRGC) version 2 experiment 4, which contains both controlled and uncontrolled images [16]. Note that while the faces in the controlled images have good image resolution and illumination, the faces in the uncontrolled images have lower image resolution and large illumination variations. In addition, facial expression changes are in a wide range from open eyes to closed eyes, from without glasses to with various glasses, from black pupils to red and blue pupils, from white skin to black skin, and from long hair to wearing a hat. All these factors increase the difficulty of accurate eye-center detection. In our experiments, we do the test on the whole training data set of FRGC 2.0, which contains 12,776 images. So there are 25,552 eyes totally to be detected. In order to train a robust eye detector, 3,000 pairs of eyes and 12,000 non-eye patches are collected as training samples from different sources.

5.1 Experiments on D-Haar Features

In this section, we use the compact Haar features after PCA (P-Haar features) as the baseline to evaluate the performance of D-Haar features. The reasons we treat P-Haar as the baseline are that (i) considering the high dimensionality of the original Haar feature space (which is 1,024 in our experiments), training on Haar features requires an extremely large scale of training date set in order to achieve decent performance; and (ii) PCA is probably the most widely used feature extraction technique with the property of optimal data representation in the sense of minimum mean-square error.

The comparison between D-Haar and P-Haar features is performed through the experiments on eye detection under three distance metrics: L1 (city-block) distance metric δ_{L_1}, L2 (Euclidean) distance metric δ_{L_2}, and cosine distance metric δ_{cos}, which are defined as follows:

$$\delta_{L_1}(X,Y) = \sum_i |X_i - Y_i| \tag{12}$$

Table 1: Comparison of eye detection accuracy between P-Haar and D-Haar under different distance metrics (ED stands for the Euclidean distance)

Method	mean(x)	std(x)	mean(y)	std(y)	ED (mean)	Detection Rate
P-Haar+L1	3.32	4.43	3.47	6.56	5.68	77.85%
P-Haar+L2	3.98	4.99	6.85	8.76	9.02	60.68%
P-Haar+COS	3.33	4.31	4.40	7.39	6.48	74.14%
D-Haar+L1	2.81	3.92	1.66	4.12	3.79	88.32%
D-Haar+L2	2.51	3.42	1.41	3.71	3.35	91.37%
D-Haar+COS	2.82	4.28	1.73	4.43	3.84	89.21%

$$\delta_{L_2}(X,Y) = (X-Y)^t(X-Y) \tag{13}$$

$$\delta_{cos}(X,Y) = \frac{-X^tY}{\|X\|\|Y\|} \tag{14}$$

where $\sum$ is the covariance matrix, and $\|\cdot\|$ denotes the norm operator.

In our experiments, the training samples are normalized to 32×32 pixels. The four-scale Haar basis vectors are applied and the dimensionality of the original Haar features is $1,024$. For the best performance, we use 150 P-Haar basis vectors under L1 distance metric, 60 P-Haar basis vectors under L2 distance metric, and 80 P-Haar basis vectors under cosine distance metric, respectively; we use 60 D-Haar basis vectors under L1 distance metric, 80 D-Haar basis vectors under L2 distance metric, and 80 D-Haar basis vectors under cosine distance metric, respectively. The detection accuracy is measured as the Euclidean distance between the detected pointed and the ground truth. Fig. 3 shows the comparison between P-Haar and D-Haar under different distance metrics.

From Fig. 3, it is observed that D-Haar features significantly outperforms P-Haar features no matter what kind of distance metric is applied. In average, D-Haar improves the detection accuracy of P-Haar by 5.17% under L1, 15.57% under L2, and 7.27% under cosine, respectively. Table 1 lists the pixel errors of eye detection in order to further show the improvement of D-Haar over P-Haar. Take the L2 distance metric as an example. D-Haar reduces the average localization error from 3.98 pixels to 2.51 pixels in the horizontal direction, from 6.85 pixels to 1.41 pixels in the vertical direction, and from 9.02 pixels to 3.35 pixels in the Euclidean distance, respectively. If we consider the eye is detected correctly when the Euclidean distance between the detected point and the ground truth is within 5 pixels, Table 1 also lists the comparison of the specific detection accuracy between P-Haar and D-Haar as well. The highest detection rate is reached by using D-Haar features and L2 distance metric, which is 91.37%.

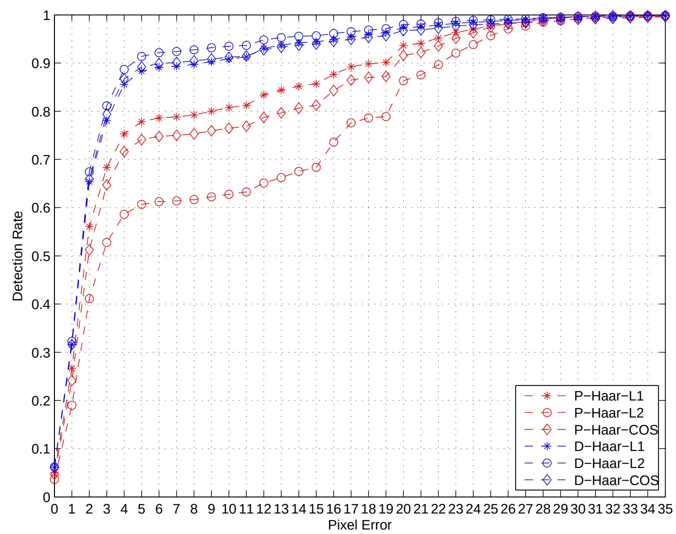


Fig. 3: Performance comparison between P-Haar and D-Haar under different distance metrics.

5.2 Performance Comparison of Eye Detection

In Fig. 4, the distribution of the Euclidean distance of detected eyes compared to the ground truth is listed, which is based on the D-Haar+L2 that is proved to be the best in accuracy. The average Euclidean distance is about 3.35 pixels. Some examples of the detection results are listed in Fig. 5.

Although the author does not think the normalized errors is a strict criterion to measure the performance of an eye detection method as explained in Section 1, it is still introduced in this section in order to make a fair comparison with other eye detectors. The normalized error is defined as follows:

$$N_{error} = \frac{|E_{det} - E_{gt}|}{D_{bio}} \times 100\% \tag{15}$$

where E_{det} denotes the detected eye, E_{gt} denotes the ground truth, and D_{bio} denotes the binocular distance.

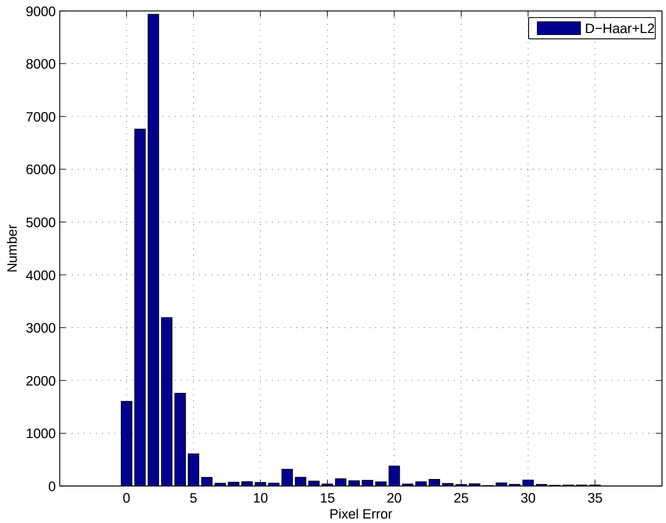


Fig. 4: Distribution of eye detection pixel errors.

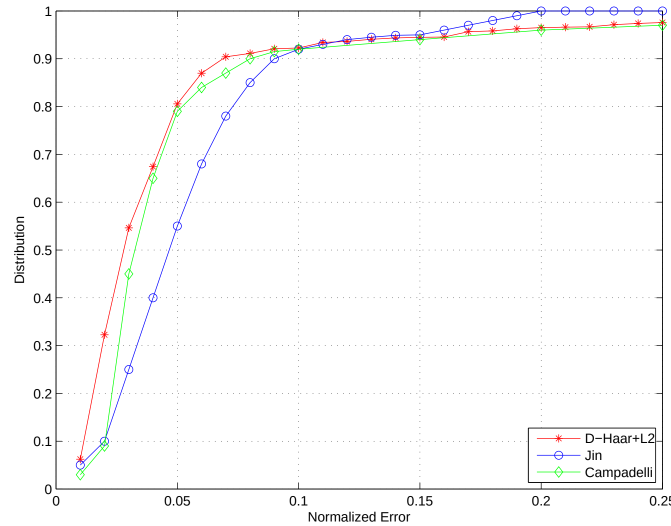


Fig. 6: Comparison of normalized detection error with different methods.

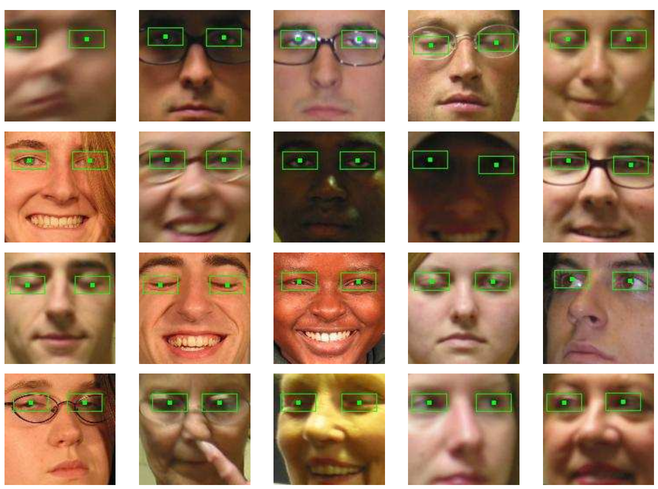


Fig. 5: Example of detected eyes.

It is hard to make an exactly fair quantitative comparison with other methods due to the different data sets used. Fig. 6 shows a typical comparison, with a hybrid classifier of Jin [17], who reported results on 3816 images of FERET database, and with the SVM based method of Campadelli [18], who reported results on 862 images of FRGC 1.0 database. Some other work reported the localization error in pixels, like Wang and Ji [19] and Everingham and Zisserman [20]. The comparison on the localization pixel error listed in Table 2 is probably a better criterion to measure the performance of different detection methods. Please note that the detection performance would decrease to some extent when the experiments do on large-scale and complicated dataset. This is can be seen from the Wang and Ji's report. When the same detection method is applied to the 3000 images of FRGC 1.0 database, the performance is worse than that on 400 images of FERET. Considering the FRGC 2.0 database we used has the huge size (12,776 images) and great complicacy (various illumination, pose, expression, and occlusions), our method indicates better and reliable performance.

6. Conclusion

In this paper, we present a novel Discriminating Haar (D-Haar) features. The D-Haar features reside in a low dimensional space spanned by a set of D-Haar basis vectors and have promising discriminating power. We then present an eye detection method using D-Haar features. Experiments on FRGC database show that (i) D-Haar features illustrate great discriminating power compared with P-Haar features and (ii) the proposed eye detection method outperforms the other state-of-the-art methods in accuracy. Future work will focus on designing an automatic face recognition system using the D-Haar features and eye detection method.

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Table 2: Comparison of eye detection error on x and y coordinates (ED stands for the Euclidean distance)

Method	Database	# images	mean(x)	std(x)	mean(y)	std(y)	ED (mean)
Jin	FERET	3,816	2.12	2.00	2.18	1.66	-
Wang and Ji	FERET	400	1.27	2.66	1.36	2.46	-
Wang and Ji	FRGC 1.0	3,000	4.99	4.58	3.17	2.69	6.40
Everingham	FERET	1,000	1.29	1.28	1.04	1.29	2.04
D-Haar+L2	FRGC 2.0	12,776	2.51	3.42	1.41	3.71	3.35

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