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# FACE RECOGNITION UNDER POOR ILLUMINATION USING HISTOGRAM EQUALIZATION AND ADAPTIVE SINGLE SCALE RETINEX

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**Түйін**

Бас компонент әдісі (БКӘ) егер бейне барынша нақты берілсе келбетті айырып тануда қолданылатын ең тиімді әдістердің бірі болып табылады. Алайда, дене қалпының өзгерісі, бет әлпет өзгерісі немесе жарықтың нашар түсуі орын алса бұл алгоритмді пайдаланудың өзіндік кемшілігі болады. Бұл мақалада жарықтың берілу өзгерісі көмегімен келбетті айырып тану деңгейін жақсарту мақсатында үш түрлі алгоритм салыстыра талданды. БКӘ қолданысынан соң бірмасштабты ретинекс алгоритмдері (БМР) және гистограммалар-ды теңестіру (ГТ) барлық кескіндемелерге жарықтың бірдей түсуі үшін пайдаланылды. Нәтижесінде, әдістерді біріктіру арқылы келбетті айырып танудың өте жоғары деңгейіне қол жеткізілді.

**Кілт сөздер**: Келбетті айырып тану, Бас Компонент Әдісі, гистограммаларды теңестіру, Бірмасштабты Ретинекс.

**Резюме**

Метод главных компонент (МГК) является одним из самых успешных методов применяемая в распознаваний лиц, если изображение достаточно стабильно. Но в случаях как изменение позы, изменение выражения лица или плохое освещение, этот алгоритм имеет ряд недостатков. На этой статье, сравнивались три различные алгоритмы с целью повышение уровня распознаваемости с помощью изменения освещения. После использования МГК, алгоритмы одномасштабный ретинекс (ОМР) и выравнивание гистограммы (ВГ) были применены к изображениям для равномерно распределения освещений для всех изображений. В итоге, очень высокий уровень распознавания было достигнуто после объединения методов.

**Ключевые слова**: Распознавание лиц, Метод Главных Компонент, Выравнивание истограммы, Одномасштабный Ретинекс.

**Abstract.** The Principal Component Analysis (PCA) is one of the most successful techniques that have been used in face recognition if the images are sufficiently regular. But this algorithm has some deficiency in some cases such that pose variation, different facial expression or poor illumination. In this paper three different methods were compared and used to increase the recognition rates of them under varying illumination. After using PCA, the other methods (Histogram Equalization and Single Scale Retinex) were applied to images to have equally distributed illumination for all images.

Eventually very high recognition rates were obtained after applying the methods by combining them.

## 1. INTRODUCTION

Face recognition have recently become a growing concern in the world as they are being used to find and determine anyone who is known as a possible threat. However, this is not their only function; they are used to identify and verify people for many different applications. Facial scans are done via many different techniques, and involve advanced software to analyze and break down specific details and features of each face [1].

The increasing interest on face recognition is mainly driven by application demands, such as nonintrusive identification and verification for credit cards and automatic teller machine transactions, nonintrusive access control to buildings, identification for law enforcement, and so on [2].

The Principal Component Analysis (PCA) is one of the most successful techniques that have been used in image recognition and compression. PCA is a statistical method under the broad title of factor analysis. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables [3].

It has been proven, both experimentally and theoretically that, in face recognition, variations caused by illumination are more significant than the inherent differences between individuals. The performance of most classical methods PCA and LDA are seriously degraded if the images expose under severe lighting variations [4].

In order to overcome illumination problem in face recognition, several methods have been used to increase the face recognition rates. In this work two different methods were used one by one or combinational. These are Histogram Equalization (HE) and Adaptive Single Scale Retinex (ASSR). Some brief information is given about them in the followings.

### 1.1 Histogram Equalization

Histogram equalization is a technique for adjusting image intensities to enhance contrast.

Let f be a given image represented as a $m_r$ by $m_c$ matrix of integer pixel intensities ranging from 0 to $L - 1$. L is the number of possible intensity values, often 256. Let p denote the normalized histogram of $f$ with a bin for each possible intensity. So

$$p_n = \frac{\text{number of pixels with intensity n}}{\text{total number of pixels}}$$

where n=0,1,…,L-1. The histogram equalized image g will be defined by

$$g_{i,j} = floor((L-1)\sum_{n=0}^{f_{i,j}} p_n), \qquad (1)$$

where floor() rounds down to the nearest integer. This is equivalent to transforming the pixel intensities, k, off by the function

$$T(k) = floor((L-1)\sum_{n=0}^{k} p_n).$$

The motivation for this transformation comes from thinking of the intensities of f and g as continuous random variables X, Y on [0, L – 1] with Y defined by

$$Y = T(X) = (L-1)\int_0^X p_X(x)dx, \qquad (2)$$

where $p_X$ is the probability density function off . T is the cumulative distributive function of X multiplied by (L – 1). Assume for simplicity that T is differentiable and invertible. It can then be shown that Y defined by T(X) is uniformly distributed on [0, L – 1], namely that $p_Y(y) = \frac{1}{L-1}$.

$$\int_0^y p_Y(z)dz = \text{probability that } 0$$

$$= \text{probability that } 0(y)$$

$$= \int_0^{T^{-1}(y)} p_X(w)dw$$

$$\frac{d}{dy}\left(\int_0^y p_Y(z)dz\right) = p_Y(y) = p_X(T^{-1}(y))\frac{d}{dy}(T^{-1}(y)).$$

Note that $\frac{d}{dy}T(T^{-1}(y)) = \frac{d}{dy}y = 1$, so

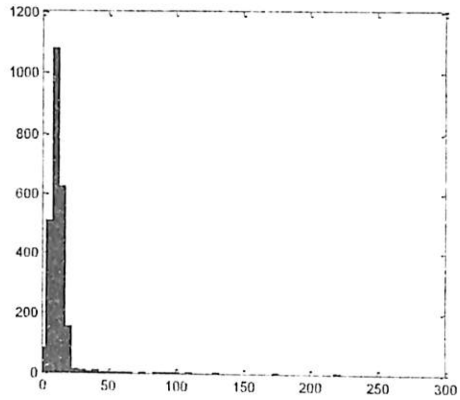
$$\frac{dT}{dx}\Big|x = T^{-1}(y)\frac{d}{dy}(T^{-1}(y)) = (L-1)p_x(T^{-1}(y))\frac{d}{dy}(T^{-1}(y)) = 1$$

which means $p_Y(y) = \frac{1}{L-1}$.

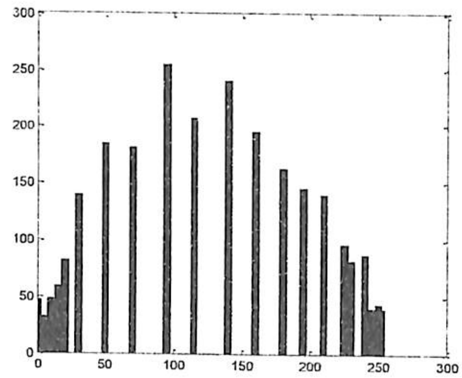
Our discrete histogram is an approximation of $p_x$(x) and the transformation in Equation 1 approximates the one in Equation 2. While the discrete version won't result in exactly flat histograms, it will flatten them and in doing so enhance the contrast in the image [5].

Matlab has the command of "histeq" itself for histogram equalization.

(a) (b)




(c)




(d)

Fig. 1. (a) a low contrast image, (b) same image after histogram equalization, (c) histogram plot of the first image, (d) histogram plot of the second image.

### 1.2 Adaptive Single Scale Retinex

Retinex theory assumes that the color perception depends strictly on the neural structure of the human vision system and compensates for illumination effects in images. The primary aim is to decompose a given image I into the reflectance image R and the illumination image L, such that at each point (x, y) in the image domain we have,

$$I(x,y) = R(x,y) \cdot L(x,y)$$

To facilitate the analysis, the noise effect is ignored here. The benefits of such decomposition include the ability to remove illumination effects of back/front lighting, enhance photos that include spatially varying illumination such as images that contain indoor and outdoor zones, and correct the colors in images by removing illumination induced color shifts.

The first step is the logarithmic conversions by $i = \log I, l = \log L, r = \log R$, and therefore

$$i = l + r$$

This step is motivated both numerically, preferring additions over multiplications, and physiologically, referring to the sensitivity of our visual system. In practice, several different algorithms based on Retinex theory are developed, and are reviewed below.

A non-iterative version of Retinex called Center/Surround Retinex algorithm was proposed by Land. The new pixel value is computed with a single filter. The filter's coefficients are computed by a surround function, whose shape is defined by the image. It includes the Single-Scale Retinex (SSR) algorithm and the Multi-Scale Retinex (MSR) algorithm.

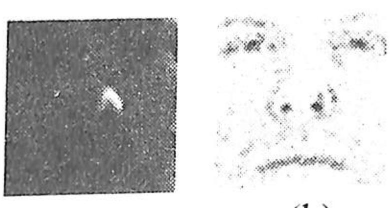
The SSR algorithm is given by

$$R_i(x,y) = \log I_i(x,y) - \log[F(x,y) * I_i(x,y)$$

where $R_i(x,y)$ is the Retinex output, the subscripts $i \in R,G,B$ represents the three color bands, $I_i(x,y)$ is image distribution in the $i$th spectral bands, "*" denotes the convolution operation, and $F(x,y)$ is the normalized surround function, and $\iint F(x,y)dxdy = 1$. Various surround function could be used. Because Gaussian function has the property of being more "regional" and offered good dynamic range compression over a large range of space constant, we used the Gaussian function

$$F(x,y) = e^{-(x^2+y^2)/c^2}$$

where c is the Gaussian surround space constant, and need to be selected in advance [6].



(a) (b)

Fig. 2. (a) a low contrast image, (b) same image after ASSR normalization.

## 2. EXPERIMENTS AND RESULTS

In this work 10 subjects which contain 16 images for each that is totally 160 frontal face images have been used taken from Yale Database B. First 8 images are high illuminated and the other 8 images are low illuminated for each subject. The high illuminated images were used as training set and the low illuminated images were used as testing set.

Methods applied to training and testing sets are given below.

1. Calculation of RR by PCA
2. Calculation of RR first applying PCA then HISTEQ to both sets.
3. Calculation of RR first applying PCA then ASSR to test set.
4. Calculation of RR first applying PCA then ASSR to both sets.
5. Calculation of RR first applying PCA then HISTEQ and then ASSR to test sets.
6. Calculation of RR first applying PCA then HISTEQ and then ASSR to both sets.

In all calculations, recognition rates were calculated according to dimensionality of PCA. That is the highest RR is obtained by using only a few number of eigenvectors in PCA. RR are shown for all cases one by one as RR vs. PCA dimensionality in the followings. All simulations were obtained by MATLAB.

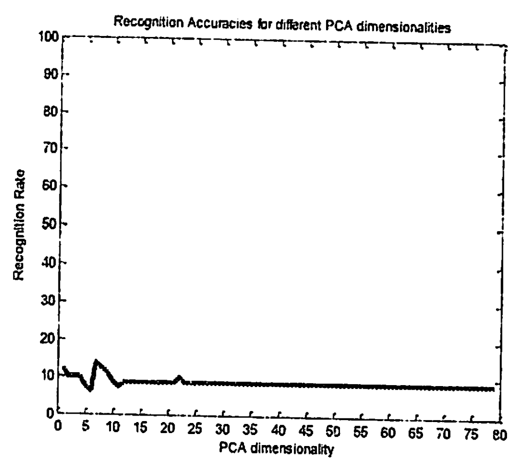



Fig. 3. PCA without filter

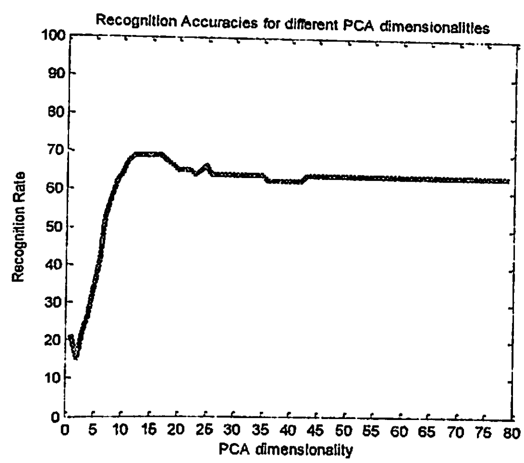



Fig. 4. PCA with HISTEQ

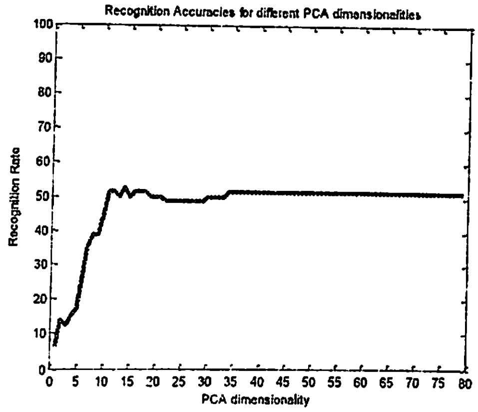



Fig. 4. PCA with ASSR to test set

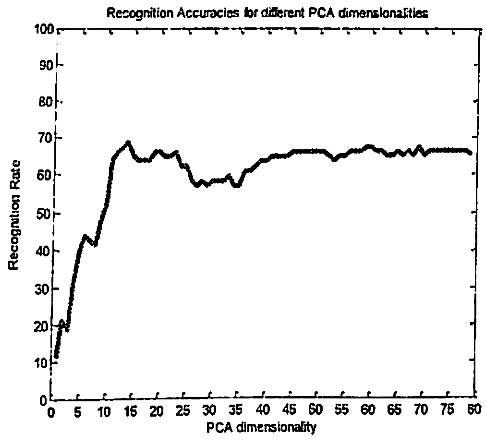



Fig. 4. PCA with ASSR to both set

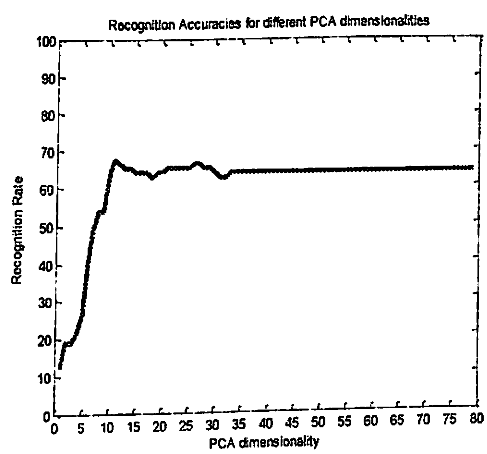



Fig. 5. PCA with HISTEQ+ASSR to test set

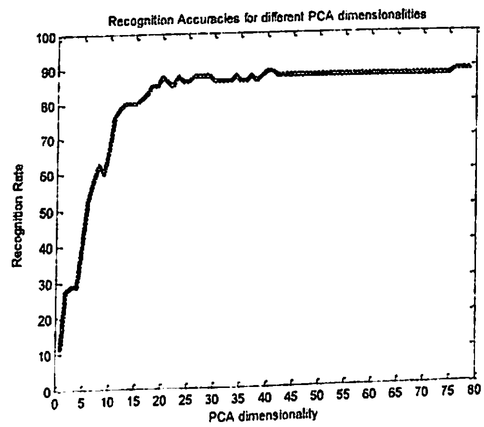



Fig. 6. PCA with HISTEQ+ASSR to both set

The results are given in the TABLE I given below.

| EXP. NO | METHOD | RR |
|---|---|---|
| 1 | PCA without filter | 15 |
| 2 | PCA with HISTEQ | 70 |
| 3 | PCA with ASSR to test set | 53 |
| 4 | PCA with ASSR to both sets | 70 |
| 5 | PCA with HISTEQ+ASSR to test set | 70 |
| 6 | PCA with HISTEQ+ASSR to both sets | 90 |

## 3. CONCLUSIONS

It can be seen in the results that the recognition rates is relatively low when they are used one by one. But combining them we can increase the RR. In this work it can be concluded that histogram equalization and adaptive single scale retinex are well-matched couple to obtain a high RR.

Actually another multiscale techniques can be found experimentally. Or the images can be classified into several sets according to their level of illumination for the next studies.

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