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AN ATTEMPT TO IMPROVE EIGENFACE ALGORITHM EFFICIENCY FOR COLOUR IMAGES

This article presents an attempt to improve Eigenface algorithm efficiency by using image pre-filtering in order to eliminate background areas of the picture and illumination influence. The background is treated as noise, so when noise is present then efficiency of the algorithm decreases. In order to eliminating this inconvenience, analysed image is pre-filtered by means of the colour classifier. The classifier eliminates pixels which have different colour than an average human skin colour on a digital photo. This causes that the Eigenface algorithm is less sensitive to background noise. The illumination influence was minimized by using hue information instead of traditionally used luminance. The main advantage of the proposed approach is possibility of using in environments where diverse image background texture and scene illumination appears. The eigenfaces technique can be applied in handwriting analysis, voice recognition, hand gestures interpretation and medical imaging.

1. INTRODUCTION

Automated object identification is very useful feature of many computer systems. One of such possibilities is a face recognition system, which can be used for user's authorisation. Automatic face image recognition is an active research topic in computer vision. Nowadays, authorisation of persons is applied in many domain of life. Unfortunately such systems require a reasonable computing power, so first promising attempts to solving these tasks have been taken only in the late 80's of the last century.

The Eigenface analysis is one of the simplest PCA based face recognition methods. It has been proposed in 1991 by M. Turk and A. Pentland [1, 2] on the basis of the face identification method presented in 1987 by L. Sirovich and M. Kirby [3]. Both of mentioned approaches are simple and fast but have many drawbacks. Unfortunately, the basic Eigenface algorithm is very sensitive to face location and image exposition. The shadows appearance, background texture and scene illumination have significant influence on quality of object recognition.

A lot of above mentioned disadvantages can be partially removed without noticeable impact on algorithm speed. It can be done when colour filtering based on image content will be carried out.

The idea based on colour image segmentation for skin detection is a relatively new from the break of the centuries. In year 2000 Wang and Youan have proposed a set of filtering rules defined with the aid of the two colour models – HSV and normalized RGB [5]. Later, in year 2003 Kovac, Peer and Solina have proposed a simpler, RGB-only based filter [6], which works faster but was significantly more sensitive to scene lighting conditions. The first filter was almost light independent, but wrongly eliminated the pixels which described skin colours. For this reason this method was rather useful for colour segmentation, but filtered image could not be used for further analysis. The second one produced well-prepared images for further processing, but worked only under certain light conditions.

In both approaches, extrinsic imaging parameters, such as pose, illumination and facial expression cause much difficulties reducing recognition rate.

Elimination of mentioned disadvantages has been described in the paper [4], where influence of artefacts on quality of object recognition has been partially decreased. In the considered paper combination of these two filters has been performed. The filter's parameters were selected on the basis of statistical analysis of the training set of human face images.

Also on the basis of [4] an attempt was taken to minimize face lighting influence by using hue channel (H) for analysis instead of a luminance (Y).

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2. SHORT DESCRIPTION OF THE EIGENFACE ALGORITHM

The presented algorithm can be divided into two parts – database building and image recognition.

The eigenface database building algorithm consists of following steps:

- ✓ Prepare the reference (training) set – all images should have the same pixel resolution and the same alignment of a face,
- ✓ Transform images into vectors and building a matrix from these vectors, where each the matrix row represents a single image,
- ✓ Calculate a mean image (average face),
- ✓ Subtract the mean image from each image in the matrix (the mean of the matrix rows will be equal 0),
- ✓ Calculate eigenvectors and eigenvalues of covariance matrix. Each eigenvector has the same dimensionality (number of components) as the original images, and thus can itself be treated as an image. The eigenvectors of this covariance matrix are so-called eigenfaces,
- ✓ Find a set of orthonormal vectors, which best describes distribution of data,
- ✓ Choose a subset from these orthonormal vectors which are associated with highest eigenvalues of covariance matrix,
- ✓ Sort these eigenvectors in ascending order – they will be called as eigenfaces.

The eigenface face recognition algorithm is executed as follows:

- ✓ Calculate eigenface components of new photo,
- ✓ Calculate a difference between mean-face and the new face,
- ✓ Multiply difference with each eigenvector (weight),
- ✓ Build a new vector of weights,
- ✓ Choose a best matched face on a basis of Euclidian distance of weights,
- ✓ Determine whether recognized face belongs to known faces class (by comparing the similarity measure with two thresholds).

3. COLOUR BASED SKIN FILTER

The pixel-colour based human skin filter [4] is used to eliminate non-skin coloured pixels. Described in the paper filtration method is based on a statistical analysis of a colour faces training set. In this approach, the two colour models have been proposed. Consequently algorithm is less sensitive to colour temperature of the light. Additionally, acceptance thresholds of colour components assure lower false rejection rate.

The proposed method allows recognising pixels belonging to face skin pixels, so filtered image can be used not only for base image segmentation (cutting out areas containing faces) but also for further processing.

4. COMBINED METHOD OF FACE RECOGNITION

4.1. IMAGE AQUISITION

It is important to have the same number of images for each person (in the class). All photographs should be the full colour (24 bit) images with the same pixel resolution, scale and aspect ratio of 1:1. The individual face should be located in the central part of the image (Fig.1).

Fig. 1. Sample face image [7].

4.2. IMAGE PRE-PROCESSING

As it was previously stated, every image is converted into a vector and each pixel is filtered by means of colour based skin filter. The pixels which belong to the range (1) are unchanged and remaining pixels are changed to the black colour.

$$\begin{aligned} &g \in [0.277;0.335] \\ &H \in [0°;34°] \cup [347°;360°] \\ &S \in [0.2;0.747] \\ &V \in [0.35;1.00] \end{aligned} \tag{1}$$

Where:

g – green channel value from normalized rgb colour model
H – hue channel value from HSV colour model
S – saturation channel value from HSV colour model
V – value (intensity) channel value from HSV colour model

The obtained image is rescaled to 0 – 255 intensity range according to the formula:

$$Y = R \cdot 0.2125 + \mathrm{G} \cdot 0.7154 + B \cdot 0.0721 \tag{2}$$

Also the alternative method have been tested, where new images have been generated using only 0 – 255 normalized Hue value (3). This step, at least in theory, should minimize the face lighting impact on a recognition process.

$$h = H \cdot 0.7083 \tag{3}$$

After this procedure image contains only initially skin coloured pixels – now in greyscale (Fig. 2b). Background pixels are eliminated eventually leaving some noise.

Fig. 2. Filtered image:
a) Luminance channel (2), b) Colour-filtered Luminance (1, 2), c) Hue channel (3), d) Colour-filtered Hue (1, 3).

From observation of the images on the Fig. 2a-2d follows that colour filtering method (1) removes most of the background pixels (Fig. 2b), what can be used to eliminate noise on the edges of face in hue channel (2c), leaving clean face image in hue channel (2d). Face represented in hue channel has no light glitches (because it may not be clearly seen, the image on Fig. 2d has been post-processed for better appearance in print).

4.3. BUILDING OF THE REFERENCE SET OF FACES

It is well-known that images can be interpreted as matrices. It is so-called bitmap form of the image. The face image is represented by a two-dimensional $N \times N$ matrix. All rows of the bitmap matrix can be concatenated, what gives one large vector of pixels, so all images of the training set are stored in a single matrix **V**, where each row of the matrix **V** represents one image.

In the first step so-called mean face is calculated:

$$\mathbf{\Psi} = \frac{1}{M}\sum_{i=1}^{M}\mathbf{\Gamma}_i \tag{3}$$

where:
$\mathbf{\Psi}$ – a mean face vector,
M – number of vectors (face images) included in the matrix **V**,
$\mathbf{\Gamma}_i$ – the vector number i from the matrix **V**.

For the subset of the images gathered in the database [7], this operation generates a mean face image (Fig. 3) which is a set of a common face features.

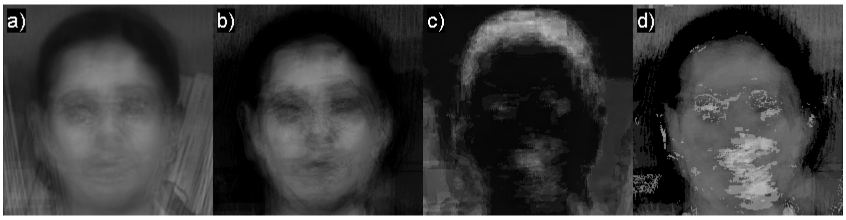

Fig. 3. Mean face generated using:
a) Y channel (2), b) filtered Y channel (1, 2), c) H channel (3), d) filtered H channel (1, 3).

From the images on Fig. 3 follows that average face image even with colour filtering still has some background artefacts, and that average face from colour–prefiltered hue channel has more sharp edges and has more constant values over its area (except light areas of the red colour having hue value less than 0°).

In the successive step the difference vector $\mathbf{\Phi}_i$ between a given vector $\mathbf{\Gamma}_i$ and the mean face vector ψ is calculated:

$$\mathbf{\Phi}_i = \mathbf{\Gamma}_i - \mathbf{\Psi} \tag{4}$$

Finally, the global vector is formed:

$$\mathbf{A} = \left[\mathbf{\Phi}_1, \mathbf{\Phi}_2, \ldots \mathbf{\Phi}_M\right] \tag{5}$$

So, all images of the training set are stored in a matrix **A**.

In the next step the square covariance matrix $\mathbf{C} = \mathbf{A}^T\mathbf{A}$ should be formed. Unfortunately, traditional covariance matrix calculation method is computationally infeasible even for small number of training images, because the covariance matrix **C** has to have the large dimension: $N^2 \times N^2$. For this matrix N^2 eigenvectors and eigenvalues can be calculated. In practice, the training set includes only from 100 to 200 face images. For this reason another approach is commonly used [1, 2].

We observe than eigenvector decomposition of the matrix **C** can be performed by mean of the formula [2]:

$$\mathbf{C}v_i = \mathbf{A}^T\mathbf{A}v_i = \lambda_i v_i \tag{6}$$

where:
v_i – the eigenvector number *i* of the covariance matrix **C**,
λ_i – the eigenvalue number *i* of the covariance matrix **C**.

However, as it has been above stated, the matrix **C** is a very large matrix. On the other hand the matrix **C** is a symmetrical. Its causes, that instead of the matrix **C**, other calculations can be proposed [2].

Consider the eigenvectors (6) of the covariance matrix **C**. Let both sides of the equation (6) will be multiple by the matrix **A**, then:

$$\mathbf{A}\mathbf{A}^T\mathbf{A}v_i = \lambda_i\mathbf{A}v_i \tag{7}$$

Now, it is easily to see that the expression $\mathbf{A}v_i$ describes the eigenvectors of the matrix **C**.

In the next step the two-dimensional $M \times M$ matrix **L** is formed:

$$\mathbf{L} = \mathbf{A}^T\mathbf{A} \tag{8}$$

The training set has in practice limitations to 100-200 images, hence $M < N^2$ and calculations become easier.

The matrix **L** is symmetrical and elements of the matrix **L** are determined as follows [2]:

$$l_{mn} = \mathbf{\Phi}_m^T\mathbf{\Phi}_n \tag{9}$$

Taking into account above mentioned considerations, for the matrix **L** we can obtain the *M* eigenvalues and *M* corresponding eigenvectors, which might be used to calculate eigenfaces.

While in original method the eigenvectors of the matrix **C** are the eigenfaces it's not true in the Turk and Pentland's method. Here having *M*' eigenvectors v_i of the matrix **L** it is possible to calculate eigenface using the formula:

$$u_i = \sum_{i=1}^{M} v_{ik}\mathbf{\Phi}_k, \qquad i = 1,\dots M \tag{10}$$

where:
u_i – the eigenface number i ,
v_{ik} – the k^{th} value of the i^{th} eigenvector of the matrix **L**,
$\mathbf{\Phi}_k$ – the k^{th} difference between mean-face and face number *k* (the formula (4)).

In the final stage so-called the weight vector $\mathbf{\Omega}$ is built. This vector characterise the contribution each eigenface, treating the eigenfaces as the basic set feature (eigenface) share in the given face:

$$\mathbf{\Omega}^T = [\omega_1 \quad \omega_2 \quad \omega_3 \quad \cdots \quad \omega_{M'}] \tag{11}$$

The number of elements which form the vector $\mathbf{\Omega}$ depends on the number of the highest eigenvectors *M*'. The number *M*' is selected by user. Each element of the vector (11) is computed as follows:

$$\omega_k = u_k^T \mathbf{\Phi}_i, \qquad k = 1,\ldots,M' \tag{12}$$

where:

u_k – the eigenface number k.

4.4. FACE RECOGNITION

When the new face image is taken then appropriate procedure is carried out, similarly to the reference data set, what was described in the sub–sections 4.1 and 4.2.

In the next step the difference between mean-face from the training set and the new face is calculated, according to the formula (4) and the appropriate eigenface is generated on the basis of the formula (9).

In the next step the Euclidean similarity measure between all weight vectors is computed:

$$d\left(\omega_i, \omega_j\right) = \sqrt{\sum_{k=1}^{M'} \left(\omega_{ik} - \omega_{jk}\right)^2} \tag{13}$$

where:

M' – number of the selected eigenvectors in the vector $\mathbf{\Omega}$,

ω_i, ω_j – the M' sized weight vectors,

ω_{ik}, ω_{jk} – the k^{th} element of the vectors ω_i and ω_j, respectively.

In the final stage, the lowest Euclidean distance $d_{\min}$ is chose and is compared to the two thresholds ε' and ε''. This comparison allows determining whether a face image was correctly recognised. The thresholds values have to be estimated experimentally:

$d_{\min} > \varepsilon'$ – the input image is not a face,

$d_{\min} < \varepsilon'$ and $d_{\min} > \varepsilon''$ – input image is an unknown face (is outside of the training set),

$d_{\min} < \varepsilon''$ – the input image was correctly recognised (is inside of the training set).

5. OBTAINED RESULTS OF IMAGE RECOGNITION

Tests were performed using a subset of the Georgia Tech face database [7]. Photos of five people have been chosen – four photos for each person. Persons have been photographed from slightly different angles and mimics. The background of photos was similar, but not identical – the minor objects were added (different textures and other artefacts). All images were manually cropped to the size of 210×210 pixels. Recognition efficiency tests were performed by means of the same set of photos which were used to build a reference database. All tests were performed using 20 eigenvectors and with the thresholds set to maximum allowable value. Table 1 presents the results of investigation. In these tests different combinations of colour filtration and image representation methods were checked.

Table 1. Test results.

Method	***Efficiency***
Base (Luminance) (2)	70%
Hue instead of Luminance (3)	65%
Luminance with colour pre-filtering (1, 2)	90%
Hue with colour pre-filtering (1, 3)	95%

As can be clearly seen from the results given above, colour based background elimination had a major impact on eigenface algorithm efficiency. The use of hue value instead of intensity, gave even better results by minimizing the influence of the light conditions and even despite the fact that using only the hue instead of the luminance (without colour filtering) gave worse results than reference methods. It was mostly due to the fact, that face database included images in the JPEG format, which had high compression noise in the colour domain (so-called compression artefacts), but this noise was located mainly in the background area. For that kind of images the appropriate colour filtering can be proposed, what has been presented in the paper.

6. SUMMARY

Eigenface method itself is not very efficient although it is fast and does not require a lot of computing power. The two main disadvantages of this method are connected with a fact that this method analyses whole image and not only a single object – face. Colour filtering helped to solve problem with taking background into account while analysis, but still there is a problem with face placement and scaling. Test results prove that combining eigenface with colour based filtering was a step in the right direction. Method proposed in this paper gives better image recognition level, than reference techniques presented in the works [5,6]. Possibly interesting results, with higher recognition level, could be obtained when thermo-photography technique will be applied. Unfortunately such databases are inaccessible and cost of thermo-cameras is too high, so the authors were unable to verify that idea.

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