A Method for Segmentation of Local Illumination Variations and Photometric Normalization in Face Images

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Abstract. In this paper we present a method for the automatic localization of local light variations and its photometric normalization in face images affected by different angles of illumination causing the appearance of specular light. The proposed approach is faster and more efficient that if the same one was carried out on the whole image through the traditional photometric normalization methods (homomorphic filtering, anisotropic smoothing, etc.). The process consists in using an algorithm for unsupervised image segmentation based on the active contour without edges approach with level set representation model for localization of regions affected by specular reflection combined with a normalization method based on the local normalization that considers the local mean and variance into the located region. The performance of the proposed approach is compared through two experimental schemes to measure how the similarity is affected by illumination changes and how the proposed approach improves the effect caused by these changes.

Keywords: image segmentation, photometric normalization.

1 Introduction

Face recognition algorithms consist in three major parts: Face detection, normalization and face identification [1]. Face recognition starts with the detection of face patterns in sometimes cluttered scenes, continues normalizing the face images to attenuate or eliminate geometrical and illumination problems, then these faces are identified using appropriated classification algorithms, and finally results are post-processed using model-based schemes and logistic feedback [2].

One illumination effect that might cause particular problems in the recognition process is the local reflection of light in the face. Recently many appearance-based algorithms have been proposed to deal with the problem [3-6]. These algorithms work well, but are computationally expensive.

To find a method to efficiently and quickly solve these problems that obtains face images without the specular illumination effect and maintaining the features necessary for identification is a challenge.

In this paper we present a new approach to perform a detection of regions affected by the specular illumination effect by means of a bi-class unsupervised texture image

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segmentation method using active contour and connected component analysis and an algorithm proposed by us to attenuate the local specular light through the filtering of the segmented regions by mean value of pixels in the neighbor regions. The first contribution of this paper is the fact that we use the unsupervised texture image segmentation method for region detection. And if in addition we consider that the segmentation turns into a region previously located by the face detector, the normalization process will be extremely fast.

The second contribution of this paper is the fact that this process of photometric normalization is done only in the segmented regions and not on the whole image and only in those images where the illumination problem is present; this clearly reports an important saving of time and calculation

The third contribution of this paper is the proposed method for the local normalization that consider the mean value and variance into the segmented image region by means of a very fast processing implemented through a lookup table.

The effectiveness of the proposed method was evaluated in several experiments using images from the Yale B database, taken a variety of illumination conditions. Obtained results demonstrate that the variations in the image similarity caused by illumination are successfully eliminated or attenuated.

2 Segmentation Algorithm

2.1 Active Contour for Image Analysis

There are two main approaches in active contours based on the mathematical implementation: snakes and level sets. Snakes explicitly move predefines snake points based on an energy minimization scheme, while level set approaches move contours implicitly as a particular level of a function [7].

The classic snakes [8] provide an accurate location of the edges only if the initial contour is given sufficiently near the edges because they make use of only the local information along the contour. Estimating a proper position of initial contours without prior knowledge is a difficult problem. Also, classic snakes cannot detect more than one boundary simultaneously because the snakes maintain the same topology during the evolution stage. That is, snakes cannot split to multiple boundaries or merge from multiple initial contours.

Level set theory has given a solution for this limitation, a formulation to implement active contours, was proposed by Osher and Sethian [7]. They represented a contour implicitly via a two-dimensional Lipschitz-continuous function $\phi(x,y):\Omega \to \Re$ defined on the image plane. The function $\phi(x,y)$ is called *level set function*, and particular level, usually the zero level, of $\phi(x,y)$ is defined as the contour.

The advantage of using the zero level is that a contour can be defined as the border between a positive region and a negative region, so the contours can be identified by just checking the sign of $\phi(x,y)$.

Among the different active contours approaches for image segmentation we based our work on the Active Contour without Edges Model. This is a variable model for

2-phase image segmentation. The basic idea is to look for a particular partition of a given image into two regions, one representing the objects to be detected and the other representing the background, if we consider Ω as a bounded open subset of $\Re^2$, with $\partial\Omega$ the boundary, we seek for $\inf F(c^+, c^-, C)$:

$$F(c^+,c^-,C) = \mu \cdot length(C) + \lambda^+ \int_{in(C)} \left|u_0(x,y) - c^+\right|^2 + \lambda^- \int_{out(C)} \left|u_0(x,y) - c^-\right|^2 \tag{1}$$

where $u_0 : \Omega \to \Re$ is the given image, c^+ and c^- are unknown constants representing the average value of u_0 inside and outside the curve and parameters $\mu > 0$ and $\lambda^+, \lambda^- > 0$ are weights for the regularizing term and the fitting terms respectively. In the level set method, $C \subset \Omega$ is represented by the zero level set of a Lipschitz function $\phi(x,y)$: $\Omega \to \Re$ such that

$$\begin{aligned} C &= \{(x,y) \in \Omega : \phi(x,y) = 0\} \\ in(C) &= \{(x,y) \in \Omega : \phi(x,y) > 0\} \\ out(C) &= \{(x,y) \in \Omega : \phi(x,y) < 0\} \end{aligned} \tag{2}$$

Using the Heaviside function H defined by:

$$\begin{aligned} H(x) = \{&1, \text{ if } x \geq 0 \\ \{&0, \text{ if } x < 0 \end{aligned} \tag{3}$$

We can replace the unknown variable C using eqs. (2) and (3), then the energy functional $F(C, c^+, c^-)$ is transformed to:

$$\begin{aligned} F(H(\phi), c^+, c^-) = \mu\left(\int_\Omega \left|\nabla H(\phi)\right|\right) + \lambda_1 \int_\Omega \left|u_0 - c^+\right|^2 H(\phi)dx + \\ + \lambda_2 \int_\Omega \left|u_0 - c^-\right|^2 (1 - H(\phi))dx \end{aligned} \tag{4}$$

2.2 Segmentation

The main purpose of our method is the segmentation of region affected by non-uniform illumination. Therefore, we need a modification of the Active Contour without Edge model defined on eq.(4), where u_0 is a multispectral image , u_0^i stands for each one of the image features (bands) and $\overline{c_+} = \left\{c_+^i\right\}_{i=1}^N$, $\overline{c_-} = \left\{c_-^i\right\}_{i=1}^N$ are vector where the i^{th} component represent the pixel values average inside and outside of u_0^i respectively. We can see these changes in the equation (5):

$$F(H(\phi), \overline{c_+}, \overline{c_-}) = \mu\left(\int_\Omega \left|\nabla H(\phi)\right| dx\right) + \tag{5}$$

$$+\int_{\Omega}\frac{1}{N}\sum_{i=1}^{N}\lambda_{-}^{i}\left|u_{0}^{i}-c_{-}^{i}\right|^{2}(1-H(\phi))dx+$$

$$+\int_{\Omega}\frac{1}{N}\sum_{i-1}^{N}\lambda^{i}+\left|u_{0}^{i}-c_{+}^{i}\right|^{2}H(\Phi)dx$$

For this algorithm implementation we have been based on [9] where it is proposed a way for implementing optimization problems based on level set representation. When we apply it to solve the functional (eq. 5) the computational cost decreases substantially. Besides, our solution does not need to solve the Euler-Lagrange equation because it computes the energy directly on the functional and analyzes the energy variation when we move a point from inside to outside of the contour or vice versa.

We can approximate the length term $\int\left|\nabla H(\phi)\right|dx$ by:

$$\int\left|\nabla H(\phi)\right|dx\approx\sum_{i,j}\sqrt{(H(\phi_{i+1,j})-H(\phi_{i,j}))^{2}+(H(\phi_{i,j+1})-H(\phi_{i,j}))^{2}} \tag{6}$$

where $\phi_{i,j}$ is the value of ϕ at the i,j th pixel. Given an initial partition $\phi>0$ and $\phi<0$ denoted by ϕ_1 and ϕ_2, assuming that there are *m* points in ϕ_1 and *n* points in ϕ_2 : let c_i, F_i be the average and energy for ϕ_i, i =1, 2.

If P is the point we want to analyze and its value is x, then if $P\in\phi_1$ the energy variation when we move P from ϕ_1 to ϕ_2 can be computed as:

$$\Delta F_{12}=(x-c_2)^2\frac{n}{n+1}-(x-c_1)^2\frac{m}{m-1} \tag{7}$$

Similarly, if P changes from ϕ_2 to ϕ_1, the change of energy is:

$$\Delta F_{21}=(x-c_1)^2\frac{m}{m+1}-(x-c_2)^2\frac{n}{n-1} \tag{8}$$

According to the needs and characteristics of the image to be segmented it can use or not the length term (8).

Without its consideration our algorithm can be summarized in 5 principal steps:

1. Give any initial partition of the image, set ϕ=1 for one part, and ϕ= -1 for the other part. Calculate initial c_1 and c_2 values.
2. For each image pixel, computes the energy variation on the functional moving the point from ϕ_1 to ϕ_2 or vice versa. If this variation is less than cero, then the value of the function evaluated in this point is changed to its opposite, i.e. if the value of the function was 1 it turns into -1.

3. Apply the connected component filter to the function to eliminate the noise less than a specific size.
4. Recalculate c_1 and c_2 values taking into account the new function ϕ.
5. Repeat steps 2, 3 and 4 while energy decreases.

In case of consider the length term (8), first we apply the algorithm as we have seen before and later, we apply it but this time in the step 2 to calculate the energy variation we take into account the change occurred in the length when we move the point from ϕ_1 to ϕ_2 or vice versa.

3 A Fast Local Photometric Normalization Method

The following proposed method is based on the local normalization algorithm that standardizes the local mean and variance of an image [10], [11]. In our approach we make a filtering by the mean value of the pixels of regions located outside the segmented regions which contains the image parts affected by low frequency illumination effect (specular light) calculated by the expression:

$$I_{(i,j)f} = I_{(i,j)} - \frac{\overline{X}.p}{I_{(i,j)0}} \tag{9}$$

Where, $I_{(i,j)0,}$ is the original value of a pixel located at the position i,j of the segmented region containing the part of image affected by illumination.

$I_{(i,j)f}$ is the normalized value of a pixel affected by illumination at the position i,j of the segmented region.

$\overline{X}$. is the mean value of vector formed by pixel values contained in the face region located outside the segmented region that contains the part of the image affected by low frequency illumination effect (specular light). See Fig 1.

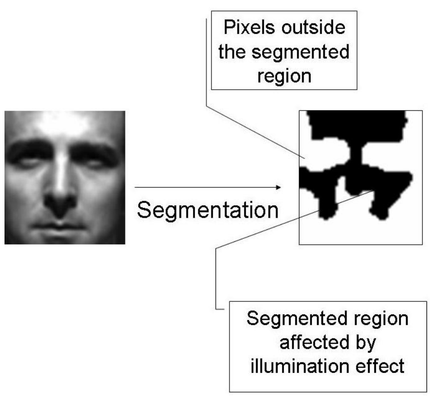

Fig. 1. Distribution of pixel values took for photometric normalization outside and inside of the segmented region

Table 1. Distance intervals and its corresponding coefficients p

No. of interval	Distance Interval	Coefficient p
1	1.2 - 1.5	10
2	1.5 - 1.8	40
…	…	…
20	6.9 - 7.2	760

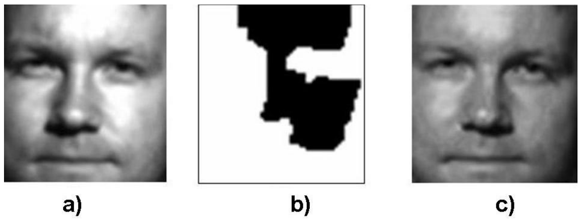

Fig. 2. Example of face image normalization in the Yale B database using the proposed method; a) original image, b) segmented region, c) normalized image

p. is the coefficient that depends of the Euclidean distance between the mean value and each value of the image inside the segmented region, the values of p are increased on a fixed quantity together with the distance interval, Table 1 shows the distance intervals and their corresponding coefficients used by us.

Taking in to account that the segmentation extracts pixels affected by illumination surrounded by non affected pixels, the normalization algorithm works with the values of these non affected pixels, the effect is the change of pixel values inside the region in function of the mean value calculated, without lost of information (see Fig 2).

4 Experiments

4.1 The Yale B Database

We experimented the proposed approach in images from Yale B database [12].

The Yale B database contains 64 different illumination conditions for 10 subjects. The illumination conditions are a single light source, the position of which varies horizontally and vertically. For the evaluation of the effectiveness of the detection process we take a test set composed by 50 images. We take 5 images per subject containing the low frequency illumination effect (specular light). Fig 3 shows an example of used images.

Fig. 3. Example of 5 images per subject with low frequency pixel values in some areas of images (specular light)

4.2 Evaluation of the Performance of Segmentation Combined with the Photometric Normalization

With generated images we compared the results in two experimental schemes. The idea was to measure how the similarity is affected by illumination changes and how the proposed approach improves the effect caused by these changes. Normalized correlation has been chosen as it has proved to be a successful similarity measure in face recognition [13]. For identical images it takes the maximum value equal to unity.

Face detection is achieved trough the Viola and John's algorithm [14], and are implemented at the OpenCV library [15]. There are several advantages offer by this method: The image representation called integral image, allows a very quickly computation of the features used by the detectors. The learning algorithm based on Adaboost, allows to select a small number of features from the initial set, and to obtain a cascade of simple classifiers to discriminate them [14]. A cascade of detectors was used to detect the faces.

To obtain geometrically normalized images we implemented an algorithm [13] that consists of the following steps: Smoothing, rotating, scaling and resampling the input image. The smoothing is performed by convolution with a Gaussian Filter of size5x5, the rotation and scaling outputs an image of size 55 rows x 51 cols. The left-eye is mapped onto the pixel position (19, 38) and the right-eye is mapped onto the pixel position (19, 12).

We compared results obtained in two different representation spaces, one in the image domain and other in the frequency domain using an illumination insensitive representation [13] based in the complex first derivative image to highlight the high frequency content and transformed it to the frequency domain and extracted the real part as illumination insensitive representation.

For the time consuming evaluation we compared the time taken by our method to normalizing of images affected by illumination taking as the region to be normalized the whole image, against the time consumed by four traditional algorithms of photometric normalization [16] (homomorphic filtering, anisotropic smoothing, isotropic smoothing and multiescale retinex) applied to whole image.

For the evaluation of the improvement of the classification task we evaluate our method in a face identification system based in the PCA method [17], since it has demonstrated inconsistent performance when the images have illumination problems [18].

For the evaluation we took one image per person from the mentioned database for the training set and comparing images with illumination problems and images photometrically normalized by our method. In the experiment we made a "close set" identification which evaluates the rate at which an individual in a database is correctly identified. We used the Cumulative Match Characteristic curve (Correct Rate vs. Rank) to analyze the behaviour of the proposed approach . A query is regarded as correct if the true fingerprint is contained in the list outputted by the algorithm

The correct rate is the rate of correct queries to all queries. The rank is the size of the list outputted by the algorithm. For all algorithms, the correct rate increases when the rank increases.

5 Experimental Results

The distributions of normalized correlations were compared in 4 different combinations. In Table 1 we show the different variants of normalized correlations and results of their comparison. We can see that when we applied the proposed approach and compared the normalized correlations in the image domain, we obtained a significant increase of the correlation coefficients of all normalized images respect to the original image.

Table 2. Normalized correlation and its comparison in Yale B database

Correlations	Description	*Nc*
In the image domain		
A	10 subjects against the same subjects using 5 different images	0.80
B	10 subjects against the same subjects using 5 different images (with previous photometric normalization).	0.89
In the frequency domain		
C	10 subjects against the same subjects using 5 different images	0.95
D	10 subjects against the same subjects using 5 different images (with previous photometric normalization).	0.99

A similar result is obtained using the representation in the frequency domain, in this case we obtained high correlation coefficients in both correlations, in concordance with results obtained by Garea and Kittler [12] but when applied the proposed approach the correlation coefficients reached nearer values to one.

The time consuming comparison (Table 2) shows that the proposed normalization method is faster than others traditionally used in computer vision even when it is applied to whole image. Taking in to account that the application of the proposed method will be only in those regions affected by illumination the time processing will decrease significantly.

The experimental results in identification (Fig 4) demonstrate that a high accuracy in the matching process is achieved when the images are previously normalized by our method.

Table 2. Comparison of averages of time consuming in the normalization process in milliseconds

Proposed method	Homomorphic	Multiescale	Anisotropic	Isotropic
0.1	3.4	3.5	10.0	0.8

6 Conclusions

The proposed method of segmentation and photometric normalization offers a set of advantages, the process is carried out only on those affected regions, and as a result we obtain a good save of time with a low computational cost.. The total save of

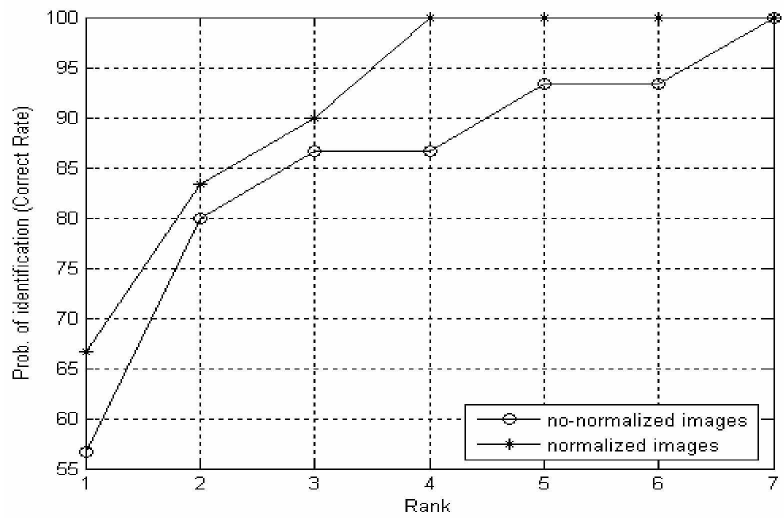

Fig. 4. Cumulative Match Characteristic curve in the Face identification system based on PCA approach

computational cost might be measure not only in the quantity of pixels that it avoids to process and also in the fact of having avoided the use of operations with high computational cost like the logarithms and the transformations to the frequency domain.

The proposed method might be used as a previous step in the general face recognition process and also as an independent process for the improvement of the visual effect of face images.

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