

Face Recognition Using Low Light

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Submitted: 15-05-2022

Revised: 20-05-2022

Accepted: 25-05-2022

ABSTRACT

Face detection has been well studied for many years. One remaining challenge is to detect faces from low-light images. The brightness of the image captured under extremely low-light conditions could be very low and the contrast will be severely reduced. It is easy to confuse feature extraction and affects the performance of face detection. In this paper, we propose a single-stage low-light face detection method. First, we design an improved MSRCR method to increase the image quality under the condition of ensuring that the colors of the image are not distorted. It shows a better enhancement effect than other methods in the DARK FACE dataset, especially since the low-resolution face details are well preserved. There are several small, blurred, and partially occluded faces. To address this, the Pyramidbox algorithm is a very effective face detection algorithm. Moreover, we conduct multi-scale tests to further develop the performance of the model and integrated the results through the Soft-NMS method to obtain final results. Integrating these techniques, this paper has achieved high accuracy and obtained excellent results in the face detection task of the DARK FACE dataset.

I. INTRODUCTION

One of the most crucial problems in face recognition practice is the variations of light intensity in input images processed by FaReS (Face Recognition System). In such a situation we have to deal with two types of complications in the area of the face and its background. The first one is related to local shadows, while the second one is associated with so-called global shadows. Local shadows change the form of individual parts of the face (nose, mouth, and eyes) and distort the boundaries of the face area. Global shadows significantly reduce the discrimination of various face areas against the general background and/or completely hide them. Such kinds of problems strongly influence the accuracy of FaReS

operation, thus this is the main reason for the lasting interest of face recognition specialists [1-11]. Analysis of the literature leads to the observation, that the problem is still unsolved in a satisfactory way. In this paper, we focus on methods involving the dimensionality reduction approach. The authors of [1] show that to solve recognition tasks using the PCA and LDA, FILPs should be transformed into spectral features using two-dimensional DCT (2DDCT). At the same processing stage, the low-frequency spectral components are removed, as corresponding to „shadow” components. In [1] the authors proposed the following procedure involving one-dimensional PCA and LDA.

II. RELATED WORK

Related Work The focus of this paper is to propose a face detection method for low-light images and it is closely related to two aspects: low-light image enhancement and face detection. Low-light image enhancement. Low-light image enhancement has always been an important means to improve image perception quality [20]. The common enhancement methods can be divided into two categories [37]: 1) image restoration based on physical models; 2) image enhancement based on image processing techniques. For the first category, by establishing and inverting the image degradation process to obtain the best estimate of the clear image [12, 31], and the second category directly improves contrast and highlights details by global or local pixel processing, regardless of the cause of color cast and image degradation [15]. Many efficient solutions are frequently designed based on the retinex theory [17]. It assumes an image as a combination of a reflectance map that reflects the physical characteristic of scene objects and a spatially smooth illumination map. Based on this theory, algorithms were designed to focus on resolving the ambiguity between illumination and reflectance by imposing certain priors on a variational model based on empirical observations

[7, 8, 11, 19]. There are many algorithms based on retinex theory such as single-scale retinex (SSR), multi-scale retinex (MSR), and multi-scale retinex with color restoration (MSRCR) [15]. In this paper, we constantly adjust and improve the MSRCR algorithm to find a low-light image enhancement method that best matches the DARK FACE dataset, which not only improves the perceived quality of the original image but also ensures that the subsequent face detection algorithm can exert more stable performances

Characteristics of images used in experiments

The literature review shows that most of the reported experiments in the area of facial portrait recognition in the presence of variable lighting conditions are conducted on the Yale database [12] as it seems to be a de facto standard in the scientific community. Complete Yale database includes original Yale B images and its extension called Yale B+[12]. In experiments we used 2452 out of 2470 images from Yale B and Yale B+ sets, containing the central part of the face area of 38 subjects (18 images were omitted since they cannot be read from files published on web site [12]). All images are stored in grayscale in matrices of 192×168 pixels, divided into 6 sets, labeled Subset 0 Subset 5, respectively. Images in Subset 0 have no blinks, and shadows and features ambient lighting. Images in Subset 1 Subset 5 were obtained by modeling the spatial movement of a light source, hence containing various variants of shadows – flashes (Subset 1 and Subset 2), local shadows (Subset 3), and lateral shadows (Subset 4 and Subset 5), as well as global shadows (Subset 5). The most difficult for recognition are images from Subset 3 Subset 5. Figure 1 presents example images from these sets.



Fig.1. Selected images from the Yale database

Face image preprocessing

It is obvious that without brightness equalization of test images the recognition rate will

be very low. As shown in [1-9], the methods of brightness enhancement (shown in Fig.2) can employ gamma correction or perform a logarithmic transformation on pixel intensities. However, this procedure must respect such parameters of the input image as mean value, local brightness, boundaries of shadows, as well as contrast. Unfortunately, such a procedure may have a negative influence on recognition accuracy. Figure 2 presents original images influenced by different lighting conditions together with results of applying one of two enhancing procedures: gamma correction (G) and brightness logarithm (Log). Observed distortions (like not removed shadows, introduced new bright spots, loss of contrast, noise) are visible in resulted images – especially when compared to original images. Even though the boundaries of different parts of the face can be easily detected, the anthropometric parameters of faces may be successfully explored. It is also visible that gamma correction and logarithmic transformation of the original image unveil different parts of the face, originally hidden in the shadow, leading to the improvement of the recognition rate. Both procedures can be easily described using the following formulas. Let i be an image of size $M \times N$ pixels, containing values from the range $\langle 0, 255 \rangle$. The gamma correction procedure applied for changing the brightness of each pixel of the image I is implemented as follows:

$$(3) \quad i_G(m,n) = i(m,n)^\gamma, \quad \forall m=1, \dots, M \text{ and } n=1, \dots, N,$$

where: $i_G(m, n)$ – pixel after correction; γ – coefficient of power transform, $\gamma < 1$

The logarithmic transformation consists of two steps. In the first step all zero values in the image matrix are replaced by ones, so that:

$$(4) \quad i(m,n) = i(m,n) + 1, \quad \forall i(m,n) = 0.$$

In the next step the logarithm is calculated:

$$(5) \quad i_L(m,n) = \log(i(m,n)), \quad \forall m=1, \dots, M \text{ and } n=1, \dots, N,$$

where $i_L(m,n)$ – a new brightness of a pixel.



Fig.2. The results of gamma correction (G) and intensity logarithm (Log) applied on original images

Practical implementation of 2D DCT

We can define the 2DDCT in a matrix form as follows [13]:

$$Y = F1 I F2,$$

where I – the original image of size $M \times N$; Y – transformation result; $F1$ and $F2$ – projection matrices of sized $1 \times M$ and $N \times d2$, where:

$$(7) f(d_1, m) = \begin{cases} 1/\sqrt{M}, & \text{if } d_1 = 0, \\ \sqrt{\frac{2}{M}} \cos \frac{\pi(2m+1)d_1}{2M}, & \text{if } d_1 = 1, \dots, D_1 - 1, \end{cases} \quad \forall m = 0, 1, \dots, M - 1,$$

$$(8) f(n, d_2) = \begin{cases} 1/\sqrt{N}, & \text{if } d_2 = 0, \\ \sqrt{\frac{2}{N}} \cos \frac{\pi(2n+1)d_2}{2N}, & \text{if } d_2 = 1, \dots, D_2, \end{cases} \quad \forall n = 0, 1, \dots, N - 1$$

One important spectrum feature should be noted. Two-dimensional DCT allows obtaining spatial-spectral features, invariant against mirror-symmetric modification of ahead to the left and/or right in the original image plane. This fact is proved by a result presented in Fig. 3. It shows two images from Yale B set, featuring mirror symmetry of the lighting source. Original spectra correspond to regular 203 (signed) 2DDCT of both images (one is represented by dots while the other with solid lines). Absolute values of 2DDCT spectra for these images are identical. Thus, the absolute value of the 2DDCT spectrum is invariant against the mirror-symmetric transformation of face images. Please note that in practical applications of face recognition above-mentioned fact of invariance can also result in better face recognition in case of head rotation around the vertical axis, and also in case of not perfect mirror-symmetry of lighting source.

Processing algorithm.

It is essential to know that computer algorithms have the most significant role in digital image processing. Developers have been using and implementing multiple algorithms to solve various tasks, which include digital image detection, image analysis, image reconstruction, image restoration, image enhancement, image data compression, spectral image estimation, and image estimation. Sometimes, the algorithms can be straight off the book or a more customized amalgamated version of several algorithm functions.



Types of Image Processing Algorithms

Some of the conventional image processing algorithms are as follows:

Contrast Enhancement algorithm: The color enhancement algorithm is further subdivided into -

- Histogram equalization algorithm: Using the histogram to improve image contrast
- Adaptive histogram equalization algorithm: It is the histogram equalization that adapts to local changes in contrast
- Connected-component labeling algorithm: It is about finding and labeling disjoint regions

Dithering and half-toning algorithm: Dithering and half-toning include the following -

- Error diffusion algorithm
- Floyd–Steinberg dithering algorithm

Else difference-map algorithm: It is a search algorithm used for general constraint satisfaction problems. It was used initially for X-Ray diffraction microscopy.

Feature detection algorithm: Feature detection consists of -

- Marr–Hildreth algorithm: It is an early edge detection algorithm
- Canny edge detector algorithm: Canny edge detector is used for detecting a wide range of edges in images.

Richardson–Lucy deconvolution algorithm: This is an image deblurring algorithm.

Segmentation algorithm: This particular algorithm parts a digital image into two or more regions.

- GrowCut algorithm: an interactive segmentation algorithm
- Random walker algorithm
- Region growing algorithm

Advantages and Disadvantages

III. CONCLUSIONS

It was shown that the 2DDCT method together with the brightness correction, fusion of features according to the current mean value of brightness as well as the removal of low-frequency components of the spectrum allows achieving higher efficiency of recognition in case of facial portraits having illumination problems – flashes,

shadows, and very low-level of brightness. The paper presents an exact model of conducted experiments, the structure of corresponding FaReS, the implementation of its algorithm, and the results of tests executed on Yale B and Yale B+ databases. Obtained accuracy is better than the ones presented in [1-10]. Moreover, the proposed algorithm is much easier to describe and simple to implement.

IV. ACKNOWLEDGMENT

We would like to sincerely thank our Guide Dr. Ashish Baiswar sir for guiding us in all this project work and we would like to thank some of our fellow members of the Information Technology department of Shri Ramswaroop Memorial College of Engineering and Management for allowing us to do our project work.

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