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An Effective Method of Stout Face Recognition Using Genetic Algorithm For Haziness and Elucidation

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Abstract
Face recognition is one of the most significant applications of image analysis. It's a factual challenge to build a mechanical system which equals human aptitude to recognize faces. We propose a Genetic Algorithm because it solves every problems with multiple solutions. Genetic algorithm solves convex optimization problems. Using the low dimensional model for elucidation variations, we show that the set of all images obtained from a face image by hazing it and by changing the elucidation conditions forms a biconvex set. Based on optimization characteristic, we propose the genetic algorithm. Our experiments on a exigent real dataset obtained in unrestrained settings illustrate the importance of jointly modeling haziness and elucidation.

Keywords
Unimpeded Face Recognition, Genetic Algorithm

I. Introduction

FACE recognition has been an extremely researched field of computer vision for the precedent couple of decades [1]. Though momentous strides have been made in tackling the problem in forbidden domains (as in recognition of passport photographs) [1], As one of the most triumphant applications of image analysis and understanding, face recognition has recently received momentous attention, especially during the past few years[2], Currently, most of the FR algorithms are applied to databases which are collected at close range (less than a few meters) and under different levels of controlled environments, such as in CMU PIE , FRGC/ FRVT , FERET data sets. Yet, in many circumstances in real life applications, we cannot control the acquirement of face images; the images we get can suffer from poor gaining, blur, occlusion etc. which are great challenges to current FR algorithms. Yao et al. describe a face video database, UTK-LRHM, acquired from long distances and with high exaggeration. They address the magnification blur to be the major squalor. Huang et al. presented a database named "Labeled Faces in the Wild" (LFW) which has been collected from the web. Although it has "natural" variations in pose, lighting, expression, etc., there is no guarantee that such a set accurately captures the range of variation found in the real world . Besides, most objects in LFW only have one or two images which may be not enough to evaluate different FR experiments[3]. However, despite the significant progress in the last decade, the design of recognition algorithms that are effective over a wide range of viewpoints, occlusions, aging of subjects and complex outside lighting is still a major area of research. While there is a significant number of works addressing these issues, problems caused by image degradations due to other factors such as blur, noise and sampling are mostly overlooked. This is particularly surprising as such image degradations also appreciably affect the performance of face recognition systems and are often present in images and videos in real-world applications such as watch-list observing and video observation. Only recently has research community started to look at facial image degradations e.g. through facial denoising The focus of this paper is therefore coping with blur and, in particular, automatic deblurring of face images for enhancing the recognition performance. Blur affects the facade of faces in images, causing two main problems for face recognition: (i) the facial appearance of an individual changes severely due to blur as Figure 1 (a) and (b) depict; and (ii) different individuals tend to appear more similar when blurred[4] A few existing methods attempt to handle these problems. However, they are not yet acceptable when facing the significant amount of blur that is common in many real-world settings For instance, Stainvas & Intrator match a query image to artificially blurred copies of the original sharp target images catalog for identification. The method can assuage the first problem of dissimilarity caused by blur, but the second problem of similarity remains. Moreover, the target images may already be blurred themselves. Our approach is based on removing the blur from facial appearances using blind image deconvolution . The deblurred images can then be used to perform more robust recognition. Obviously, such an approach can solve both problems (i) and (ii) concurrently, but requires a Point Spread Function (PSF) that represents the blurring process[5]. In the field of blind image deconvolution, many methods have been proposed for deblurring from a single image Other methods attempt to model the smoothness of intensity changes around edges. A PSF is inferred using information derived from this smoothness using the variation of Gaussian scale, wavelet coefficient, the summation of image derivatives , or alpha values representing the object boundary transparency[5]. the effects of blur, which normally arise due to out-of-focus lens, atmospheric turbulence, and relative motion between the sensor and objects in the scene, is an important problem in image analysis applications such as face recognition. The image formation equation modeling the blurring process can be written as,

~y(n1; n2) = (y ¤ k)(n1; n2) + ´(n1; n2)

where (n1; n2) denotes the pixel location at which a 2D convolution ¤ is performed between a d1£d2 clean image y(d1£d2) and an unknown blur point-spread function (PSF) k(b1£b2), to result in a blurred image1 ~y(d1£d2)[6].

To summarize, the main technical contributions of this paper are:

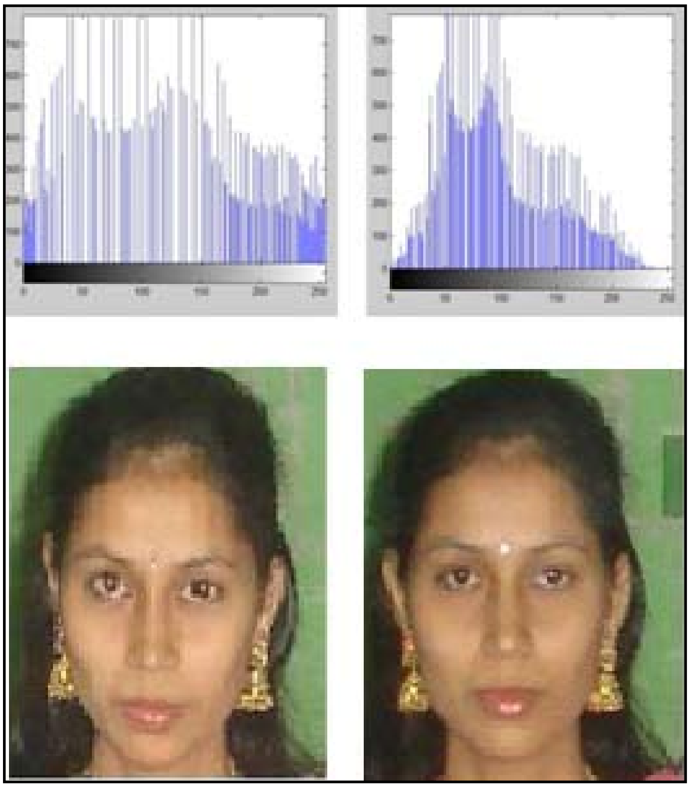
1. We show that the set of all images obtained by blurring a given image forms a convex set. More specifically, we show that this set is the convex hull of shifted versions of the original image.
2. Based on the optimistic characterization, we propose a genetic algorithm, which avoids solving the challenging and unnecessary problem of blind image deconvolution.
3. If we have additional information on the type of blur affecting the probe image, we can easily incorporate this knowledge into our algorithm, resulting in improved recognition performance and speed.
4. We show that the set of all images of a face under all blur and illumination variations forms a bi-convex set[1].

Four methods are used : i) Histogram Equalization ii) Detecting Skin iii) Filling Holes and Detecting Face iv) Face Recognition v) Putting Bounding Box around the detected Face.

II. Methods

A. Histogram Equalization

Histogram Equalization is a method in image processing of contrast adjustment using the image's histogram. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal. Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images that user would apply false-color to. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low color depth. For example, if applied to 8-bit image displayed with 8-bit gray-scale palette it will further reduce color depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher color depth than palette size, like continuous data or 16-bit gray-scale images. Histogram equalization is used to enhance contrast. It is not necessary that contrast will always be increase in this. There may be some cases were histogram equalization can be worse. In that cases the contrast is decreased.



Consider a discrete grayscale image {x} and let ni be the number of occurrences of gray level i. The probability of an occurrence of a pixel of level i in the image is

$$p_x(i) = p(x=i) = \frac{n_i}{n}, \quad 0 \le i < L$$

L being the total number of gray levels in the image (typically 256), n being the total number of pixels in the image, and $p_x(i)$ being in fact the image's histogram for pixel value i, normalized to [0,1].Let us also define the cumulative distribution function corresponding to px as

$$cdf_x(i) = \sum_{j=0}^{i} p_x(j),$$

which is also the image's accumulated normalized histogram.

We would like to create a transformation of the form y = T(x) to produce a new image {y}, with a flat histogram. Such an image would have a linearized CDF across the value range, i.e.

$$cdf_y(i) = iK$$

for some constant K. The properties of the CDF allow us to perform such a transform; it is defined as

$$y = T(k) = cdf_x(k)$$

where k is in the range [0,L). Notice that T maps the levels into the range [0,1], since we used a normalized histogram of {x}. In order to map the values back into their original range, the following simple transformation needs to be applied on the result:

$$y' = y \cdot (\max\{x\} - \min\{x\}) + \min\{x\}$$

B. Skin Detection

For the segmentation of human faces based on skin color, the key is to select the color space and its cluster. In color images, skin color is very useful information for human face. Using skin-color information effectively can reduce the amount of searching time when it needs to make sure of the region of human face. However, skin-color information is often influenced by some factors. For instance, light environment and image acquisition equipment will lead to color offset. To detect the skin regions in an image. Photos in which people are fully covered give the best results as the complexity of the code reduces and complex procedures such as neural networks or template matching are not required. But this code does a good job of identifying faces even with some skin shown in the image.

C. Filling Holes

The idea is to let MATLAB identify white blobs in an image but because of certain broken blobs they are identified as separate blobs and this makes it difficult to detect faces with accuracy. In the above picture, the chinese women's face has a big black cut running between the two eyes. and the same with the chinese man. What we would do is we would fill the gaps with white spaces so as to make it a solid white blob. MATLAB has an inbuilt function for the same known as 'imfill'. Type imfill in MATLAB help to find out more about the function.Before performing 'imfill' we need to convert our grayscale image into a binary image.'BW=im2bw(I,level);' converts the grayscale image I to a binary image. The output image BW replaces all pixels in the input image with luminance greater than level with the value 1 (white) and replaces all other pixels with the value 0 (black). You specify level in the range [0,1], regardless of the class of the input image. The function 'greythresh' can be used to compute the level argument automatically. If you do not specify level, im2bw uses the value 0.5.

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D. Face Recognition

Face recognition can be done by Genetic algorithm because of its optimisation character. Genetic algorithms are the most powerful unbiased optimization techniques for sampling a large solution space. Because of unbiased stochastic sampling, they were quickly adapted in image processing. They were applied for the image enhancement, segmentation, feature extraction and classification as well as the image generation.The constant improvement of genetic algorithms will definitely help to solve various complex image processing tasks in the future. Genetic Programming is a relatively recent technology which has been demonstrated as a versatile tool for Automatic Program Generation in a variety of applications . Many of these applications have been under conditions where a known optimal solution is determined in advance. Face recognition presents a challenging problem in the field of image analysis and computer vision, and as such has received a great deal of attention over the last few years because of its many applications in various domains. Face recognition techniques can be broadly divided into three categories based on the face data acquisition methodology: methods that operate on intensity images; those that deal with video sequences; and those that require other sensory data such as 3D information or infra-red imagery.

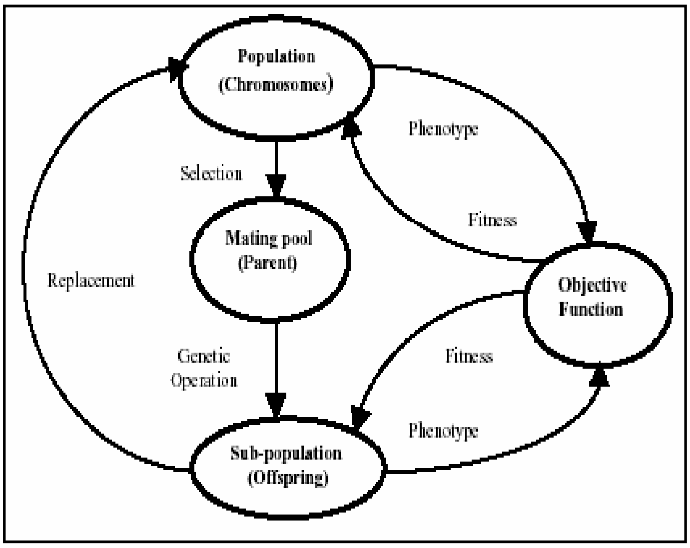

Fig. 1: A high-level diagram of the system used for face recognition

E. Putting Bounding Box

After face recognition bounding boxes will be used to show the detected faces,after this process the gender on an image can be classified using gender classification algorithm, Although several gender classification methods have been reported in the literature, gender classification has attracted less attention compared to other research topics in computer vision. Successful gender classification could be used to boost the performance of face recognition systems

III. Conclusion

A novel contrast augmentation method for distantly acquired images using Principal Component Analysis (PCA) method. The proposed algorithm decay the input image of blurred image into deblurred image and reverse the same process to restore the image as original image. The proposed algorithm can effectively enhance the quality and visibility of local details better than existing state-of-the-art methods including IRBF algorithm to recognize the blurred image and DRBF algorithm to deblur the image. For this reason here the Principal Component Analysis method is used. In Existing system FERET dataset is used with four types of blurs: out of focus, atmospheric, motion and non parametric blur. Here I used REMOTE dataset

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