Blur and Motion Blur Influence on Recognition Performance of Color Face

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Abstract: - Face recognition is an existing and one of the most prominent biometrics techniques, including the processing of images. It is widely used in many applications. The performance of such systems is directly due to face image quality. Since blur and motion blur are common imagery problems, this paper explores the influence of such disturbances on color face recognition performance. The research described in this paper compares the performance of the face recognition algorithm based on the Haar features and Local Binary Patterns Histograms when it uses color face images of good quality, images with added Gaussian blur and motion blur, as well as enhanced images.

Key-words: - Color Face recognition, Gaussian blur, Motion blur, Haar feature, LBPH algorithm.

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1 Introduction

Face recognition, besides fingerprint recognition, is one of the most popular biometric recognition techniques. It is non-invasive, relatively easy to implement from the system point of view, and very useful both in online applications (real-time face recognition) and offline applications (for example, search engines for recognizing persons from images). Nowadays it is widely used on social networks, such as Facebook, Snapchat, Instagram, etc.

The algorithms for face recognition and every face recognition system, are well-studied topics in the research community.

A face image captured and processed in an uncontrolled environment suffers from common disturbances, blur, and motion blur. These issues represent a big challenge for scientists today.

This paper explores the influence of such disturbances on color face recognition performance.

In this paper, we compare the performance of the face recognition algorithm (based on Haar features for face detection and LBPH - Local Binary Patterns Histograms algorithm for face recognition), when it uses color face images of good quality (original images), images with added noise (Gaussian blur and motion blur) and deblurred images (blur and motion blur enhancement).

2 Face Recognition Algorithm

The face recognition process can be divided into three subcategories: face detection features extraction and recognition (Fig.1), [1].

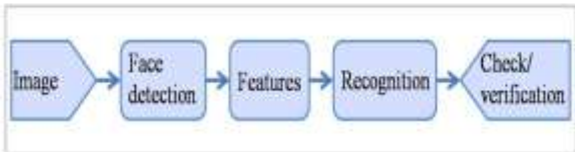

Fig. 1: Face recognition process, *[1]*.

The system workflow is as follows. The first step, face detection, [2], separates the person(s) from other image parts. Features detection extracts matching features used for recognition, [3]. The last step, face recognition, identifies the person. To achieve automatic recognition, a database of the known face data is required (gallery database) - for each person that needs to be recognized by the system, at least, one face image should be stored in the gallery database. The recognition process includes finding the best match (similarity) between the tested image and the images stored in the gallery database, [1]. The experimental setup is based on Python with the OpenCV library. OpenCV has two pre-trained and ready-to-use face recognition classifiers: the Haar classifier and the LBPH classifier, for person detection and recognition.

2.1 Face Detection Algorithm

The Face detection algorithm used in this research is based on the built-in OpenCV face detection function, in the Cascade Classification Class, which has already been trained to find a face in the image. This function uses Haar features, [4]. The most common Haar characteristics are represented by combining binary variables, which have been calculated by using several functions. The Haar feature templates shown in Fig.2 are used. Each window is placed in the image to calculate features one by one. Each feature is represented by one value obtained by subtracting pixels at the white rectangle location from pixels at the black rectangle location.

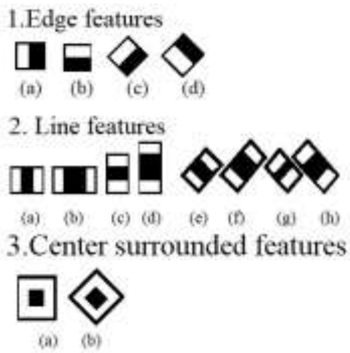

Fig. 2: Common Haar features

Fig. 3: Example of Haar features, *[5]*.

Fig. 3 presents two templates of Haar features, an example. The first one focuses on the fact that the region around the eyes is usually darker than the area of the nose and the face. The second feature relies on the fact that the eyes are darker than the area of the nose area between the eyes. Generally, the features are calculated for the image blocks. Most of the features that are obtained are irrelevant. For example, when features are calculated on the cheek area, the window becomes useless, because none of these surfaces is darker or brighter than other regions on the cheeks. Consequently, useless features are quickly discarded and only meaningful ones are retained. This technique is called AdaBoost. AdaBoost is a face detection training process that selects only those characteristics that are known to improve classification (face / non-face), [5]. Finally, the algorithm takes into account the fact that most of the region in a picture is a non-face region. With this in mind, it is better to check if the window belongs to the face region, and if not, it is immediately discarded and not processed again, so that the focus is on the area where the face is [1].

2.2 Face Recognition Algorithm

Face recognition algorithms (classifiers) require to be trained with known face images (gallery database). The training process extracts recognition features from images of known faces (subjects) and labels them.

OpenCV has three built-in face recognition algorithms, [6]:

- EigenFaces Face Recognizer
- FisherFaces Face Recognizer
- Local Binary Histograms (LBPH) Face Recognizer

This research paper uses the LBPH (Local Binary Patterns Histograms), [7], algorithm. This algorithm reduces the structure of the image by comparing each pixel with its neighborhood. First, a selected window is divided into blocks (eg. 3x3 pixels for each block), as can be seen in Fig.4. Each pixel in the block is compared with each of the 8 neighbors. Pixels are arranged along the circle, e.g. in the clockwise direction. Where the pixel center value is greater than the neighbor's value, the result is "0", otherwise it is "1". Therefore, from the 8 surrounding pixels, one can obtain 2^8 possible combinations, called Local Binary Patterns or LBP. After that, the updated pixel values are read clockwise. They are treated as a number in the binary system. Then, this number is converted to a decimal number, which represents a new pixel center value. The procedure is repeated for each pixel in the image.

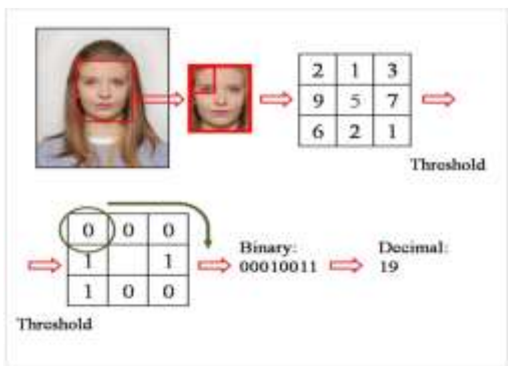

Fig. 4: LBPH example, *[5]*.

The obtained values in blocks are encapsulated in a histogram so that each block corresponds to a histogram. Finally, all histograms are connected to form one vector. It is shown in Fig.5.

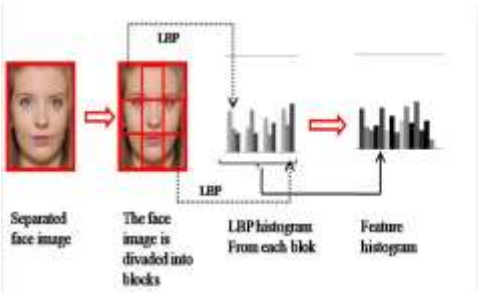

Fig. 5: LPBH, *[5]*.

Histograms define a final vector of labels, [8]. Finally, the resulting histogram connects these block histograms to form one vector of features for one image, containing all the interest features.

3 Blur and Motion Blur

3.1 Imagery Problems

Image noise is unwanted information on a digital image in the form of a random variation of color or brightness. Image noise is an undesirable by-product of image capture and obscures desired information. It can be produced by the sensor, or when a photographer accidentally moves his hand while taking a picture [9]. One of the image noise effects is an occurrence of a blur. Image blur is very usual in natural photos, originating from different factors, like atmospheric disturbances, object motion, out-of-focus camera, and camera shaking. Motion blur is caused by the sudden movement of a sensor, or the fast movement of an object, during the exposure time.

3.2 Blur Enhancement Algorithm

The most common blur representation in the image processing field is the Gaussian blur or Gaussian smoothing. It is the result of blurring an image by a Gaussian function, [10].

Test subset with added blur (blur subset) is created using the 2D Gaussian smoothing kernel with a standard deviation of 2.

A test subset with enhanced Gaussian blur has been generated from the blur subset with the method for recovering the blur kernel, [11], which is based on statistical irregularities.

This model is used together with an accurate spectral whitening formula to estimate the power spectrum of the blur. The blur kernel is then recovered using a phase retrieval algorithm with improved convergence and disambiguation capabilities. Unlike methods that rely on the presence and the identification of well-separated edges in the image, this statistical approach copes well with images containing under-resolved texture and foliage clutter. The described method does not reconstruct the latent image repeatedly and accesses the input image only once to extract a small set of statistics - the core of this technique depends only on the blur kernel size and does not scale with the image dimensions. Therefore, it is not computationally complex. Accurate estimation of the blur kernel and minimization problem is solved by the linearized Bergman iteration, [12].

3.3 Motion Blur Enhancement Algorithm

Motion blur effects are manifested as visible lines generated by the fast movement of an object in front of the recording device. A test subset with added motion blur was created by a 2D motion blur filter. One dimension is the linear motion of the camera (lens), and the other is the angle of camera motion (theta). the Parameters used for this experiment were lens 7 and theta 12. A test subset with artificially removed motion blur was generated in the same manner as the previously described de-blurring algorithm, [11], [12].

4 Experimental Results

4.1 Image Database

The database contains face images of 50 persons. All images have the same dimensions and the same orientation. Color (visible light) images subset of this database contains 11 images per rotation with different poses for each expression (neutral, smiling, boring and open mouth) and illumination (daylight, darkness, and three different light sources, frontal, left, and right lateral) of every individual. This database can be used for different experimental setups in the face recognition area [13]. Different subsets of this database were used for training and testing. Both subsets contain 30 visible light, frontal images (one per each person in the database), taken with a different subject pose - these subsets contain images with neutral and smiling expressions, randomly divided into testing and training subsets.

Test subset is used in five different forms: original, with added Gaussian blur, with added motion blur, and with enhanced motion blur.

Fig. 6: Original image, image with blur (motion, Gaussian), and deblurred images from Database

4.2 Experiment Description

The algorithm for face recognition tested in this paper detects faces by the Haar features and then does the recognition using the LBPH algorithm. The algorithm was first tested with original images, then with images containing artificially added motion blur and Gaussian blur. Afterward, it was also tested with image subsets with enhanced blur (Fig.6).

4.3 Results

Table 1. Accuracy for different blur

	ACCURACY %
Original	91.3
Gaussian blur	46
Motion blur	64.76
Enhanced Gaussian blur	64.67
Enhanced Motion blur	74

In this table, we can see that all the presented results indicate that blur and motion blur negatively influence face recognition performance, as expected.

5 Conclusion

Color Face recognition performance in biometric systems directly depends on face image quality. This paper explores the influence of blur and motion blur on color face recognition performance. the Face recognition algorithm used in the experimental part of the work is based on the Haar features and LBPH. Two sets of experiments, Gaussian blur and motion blur experiments have shown similar outcomes and led to the following conclusions.
The first conclusion is that Gaussian blur is a harder problem for color face recognition compared to motion blur presence on images. The reason for this is the fact that edges are more visible in images with motion blur, compared to Gaussian.
The second conclusion is that blur and motion blur negatively influence the color face recognition performance, as expected.
The unique conclusion is that enhanced images are more likely to be recognized by the biometric system, compared to blurred images, with the cost of more false alarms.
Our future work in this area will include more image disturbance types and new techniques for image enhancement.

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