Face Recognition with Name Using Local Weber’s Law Descriptor

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Abstract: In Image processing face recognition plays an important role in various biometric applications. WLD (Weber’s Local Descriptor) will be used for face recognition. WLD is a texture descriptor that performs better than other similar descriptors but it is holistic due to its very construction. Image is divided into number of blocks and WLD is calculated for each block and then concatenate them. This spatial WLD has better discriminatory power compared to other existing descriptor methods. It is used to represent the image in terms of differential excitations and gradient orientation histogram for texture analysis. The WLD is based on Weber’s law and it is robust to illumination change in noise and other distortions. So it effectively analyzes the facial features for accurate matching with the existing facial images in the database. The feature extraction approach will be used for both test and database images to recognize face. The face will be recognized by finding Euclidean distance between them. The proposed spatial WLD with simplest classifier gives much better accuracy with lesser algorithmic complexity than other existing face recognition approaches. Through a large number of experiments performed on FERET (Facial Recognition Technology) database, two datasets with low (20x16) and high (60 x48) resolutions from FERET database are used.

Keywords: Colour Image, Weber’s Law Descriptor, Face Recognition.

1. INTRODUCTION

Face detection can be regarded as a specific case of object-class detection. In object-class detection, the task is to find the locations and sizes of all objects in an image that belong to a given class. Examples include torsos, pedestrians. There are number of applications where face recognition can play an important role including biometric authentication, high technology surveillance and security systems image retrieval and passive demographical data collections. It is observable that our behavior and social interaction are face recognition system could have great impact in improving human computer interaction systems in such a way as to make them be more user-friendly and acting more human-like. It is unarguable that face is one the most important feature that characterizes human beings. By only looking ones faces, we are not only able to tell who they are but also perceive a lot of information such as their emotions, ages and names. This is why face recognition by face has received much interest in computer vision research community over past two decades. There are two main steps involved in recognizing names of humans presented in an image. These are face detection and name classification, which are applied consecutively. In order to exploit uniqueness of faces in name recognition, the first step is to detect and localize those faces in the images. This is the task achieved by face detection systems. As face detection is one of popular research areas, many algorithms have been proposed for it. Most of them are based on the same idea considering the face detection as a binary classification task. That is, given a part of image, the task is to decide whether it is a face or not. This is achieved by first transforming the given region into features and then using classifier trained on example images to decide if these features represent a human face. faces can appear in various locations and can also show themselves in various sizes, often a window-sliding technique is also employed. The idea is to have the classifier classifying the portions of an image, at all location and scales, as face or non-face.

2. WEBER’S LAW DESCRIPTOR FOR IMAGE REPRESENTATION

The paper proposes a simple, yet very powerful and robust local descriptor, called the Weber’s Local Descriptor (WLD). In this section we give an overview of basic WLD descriptor and its extension. WLD descriptor is based on Weber’s Law
According to this law the ratio of the increment threshold to the background intensity is constant. Inspired by this law, proposed WLD descriptor for texture representation. The computation of WLD descriptor involves three steps i.e. finding differential excitations, gradient orientations and building the histogram.

\[ \Delta I / I = K \]  
(1)

The intensity differences between its neighbours and a current pixel are constant K. By means of this the salient variations of the pattern perception of human beings within an image can be simulated. Specifically, a differential excitation \( \xi(X_c) \) of a current pixel \( X_c \), is computed. We first calculate the differences between its neighbours and the centre point using the filter \( f_0 \)

\[ V_{00} = \sum_{i=0}^{p-1} (\Delta X_i) = \sum_{i=0}^{p-1} X_i = X_c \]  
(2)

Where \( X_i \) \((i=0, 1..., p-1)\) denotes the \( i \)th neighbours of \( X_c \) and \( p \) is the number of neighbours. Following hints in Weber’s Law, then compute the ratio of the differences to the intensity of the current point by combining the outputs of the two filters \( f_0 \) and \( f_1 \) (whose output \( V_{01} \) is the original image in fact).

\[ G_{ratio}(X_c) = \frac{V_{00}}{V_{01}} \]  
(3)

We then employ the arctangent function on \( G \) ratio (*):

\[ G_{arctan}[G_{ratio}(X_c)] = \arctan[G_{ratio}(X_c)] \]  
(4)

Combining (2), (3) and (4), we have:

So, the differential excitation of the current pixel \( \xi(X_c) \) is computed as:

\[ \xi(X_c) = \arctan[\frac{V_{00}}{V_{01}}] = \arctan[\sum_{i=0}^{p-1} \frac{X_i - X_c}{V_i}] \]  
(5)

Note that \( \xi(x) \) may take a minus value if the neighbour intensities are smaller than that of the current pixel. By this means, attempt to preserve more discriminating information in comparison to using the absolute value of \( \xi(x) \). Intuitively, if \( \xi(x) \) is positive, it simulates the case that the surroundings are lighter than the current pixel. In contrast, if \( \xi(x) \) is negative, it simulates the case that the surroundings are darker than the current pixel.

2.1. Differential Excitation

One of the major components for finding the face recognition problem is differential excitation. The accuracy of the system depends on its parameter. Differential excitation is represents as \( \varepsilon(x_c) \) For the calculating differential excitation \( \varepsilon(x_c) \) of a pixel \( x_c \), calculation is performed at the pixel, the intensity differences of pixel \( x_i \) with its neighbour pixel \( i \) if considered \( i = 1, 2..., p \). Below expression are calculated as intensity follows:

\[ \Delta I_i = I_i - I_c \]  
(6)

Next calculate the ratio. Ratio performed by total intensity difference of \( x_c \) with its neighbours \( X_i \) to the intensity of \( X_c \) is determined as follows:

\[ f_{ratio} = \sum_{i=0}^{p-1} (\Delta I_i / I_c) \]  
(7)

For this differential excitation Arctangent function is used. The main function of this filter is improving performance the robustness of WLD against noise.

\[ \varepsilon(x_c) = \arctan[\sum_{i=0}^{p-1} (\Delta I_i / I_c)] \]  
(8)

The above expression \( \varepsilon(x_c) \) is depends on two different value. That is positive and negative, the positive value indicates that the current pixel is darker than its surroundings and negative value means that the current pixel is lighter than the surroundings.

2.2. Gradient Orientation

Next main parameter of WLD is gradient orientation. Both different excitation and gradient orientation is performed at the same type of pixel \( X_c \) and same arctangent function is used. Calculate the gradient orientation of the pixel \( X_c \) as follows:

\[ \theta(x_c) = \arctan[I_{x1}/I_{x0}] \]  
(9)

Gradient orientation of pixel \( X_c \) is represented as arctangent function of ratio of two intensity parameters. Where \( I_{x1} = I_x - I_3 \) is the intensity difference of two pixels on the left and right of the current pixel, \( x_c \) and \( I_{x0} = I_x - I_1 \) is the intensity difference of two pixels directly below and above the current pixel, and \( \theta \) values varies from negative to positive \( \theta \in [-\pi/2, \pi/2] \).

The gradient orientations are quantized into T dominant orientations

\[ \phi = (2\pi / T) \theta \quad \text{where} \quad t = \text{mod}(\theta / (2\pi / T) + 1/2)T \]

Where \( \theta \in [0,2\pi] \) and is defined in terms of gradient orientation computed by Eq. (9).

In case \( T=8 \). The dominant orientations are \( \phi = t \pi / 4 \), \( t = 0, 1, 2, ..., 7 \). all orientations located in the interval
\[
\phi_t = (t \pi / 4), \phi_t + (t \pi / 4) \]
are quantized as \(\phi_t\). Orientation is the gradient orientation of the current pixel.

2.3. Holistic WLD Descriptor

After calculating differential excitation and dominant orientation, WLD descriptor is build. Corresponding to each dominant orientation \(\phi_t \): \(t = 0, 1, 2... T-1\) differential excitations are organized as a histogram \(H_t\). Each histogram \(H_t\) is divided equal number of \(M\) sub histograms, and represented as \(H_{m,t}\) where \(m\) values varies from \(m = 0, 1, 2... M-1\), each with \(S\) bins. Complete above process histogram matrix is formed based on their above histogram. In these histogram each column and row are represented different ways. Each column are corresponding to the dominant direction and each row are concatenated as a histogram \(H_{m}\), and sub histogram is formed indicates \(t\), and varies from: \(t = 0, 1, 2... T-1\). Subsequently, histograms \(H_{m}: m = 0, 1, 2... M-1\) are concatenated into a histogram \(H = [H_{m}: m = 0, 1, 2... M-1]\). This histogram is referred to as WLD descriptor. This descriptor involves three important free parameters are calculated like \(T\), \(M\), \(S\) and \(T\), the number of dominant orientations, \(M\) the number of segments of each histogram corresponding to a dominant orientation and \(S\), the number of bins in each segment.

2.4. Spatial WLD Descriptor

Main difference of the holistic WLD compare to the spatial WLD, it is calculating the one extra important parameter, these parameter values depends on optimal system. In previous subsections, described basic WLD represented an image as a histogram of differential excitation organized according to dominant gradient orientations. But spatial WLD is represented an image different ways like histogram of differential excitations are collected according to their values and gradient orientations irrespective of their spatial location. The values are depends on Spatial location, the region is it is important factor for better description.

If considered one image, in these image are taken two different regions with same differential excitation and gradient orientation will contribute to the same bins in the histogram. Introduce important parameter is spatial information; normally image will not be discriminated by WLD descriptor. To enhance the discriminatory power of WLD descriptor, these methods are used. Spatial information involves, if taken one image and divide image into number of blocks and calculate the WLD for each block and form a spatial WLD.

In previous holistic method are calculating only three parameters one term missing but SWLD are finding extra parameter is number of blocks. These four parameters are: \(T\), \(M\), \(S\) and the number blocks. This performs better because it captures the local information in a better way, which is important for recognition purpose. But this approach introduces another parameter: the size of blocks. The optimal value of this parameter can lead to better recognition results.

3. FACE IMAGE IN COLOUR

Two publicly available offline signature corpuses were used. The first database is the offline sub corpus of the MCYT database. It includes 75 signers from four different Spanish sites. The corpus includes 15 genuine signatures and 15 simulated forgeries for each signer. Genuine signatures were acquired in two sessions. Forgers are given the signature images of clients to be forged and, after training with them several times, they are asked to imitate the shape. All signature data were acquired with the same inking pen and the same paper templates, over a similar pen tablet. The paper templates were scanned at 600 dpi.

The second database is the GPDS960GraySignature corpus. This corpus contains 24 genuine signatures and 24 simulated forgeries from 881 individuals. The genuine signatures were taken in just one session. The repetitions of each genuine signature and forgery specimen were collected, allowing each user his or her own pen on sheets of white A4 paper. Each sheet provided two different box sizes for the signature: the first is 5 cm wide and 1.8 cm high and the second is 4.5 cm wide and 2.5 cm high.

For experiments, we used two dataset with low (20x16) and high (60x48) resolutions from FERET database [5], which is one of the challenging databases for face recognition. This database contains image corpus that is collected to evaluate the algorithms of face recognition by standardized procedures and test. The images in the database are frontal, left or right profiles and could have some variations in pose, expression and lightning. For experiments, we used two sets: \(fa(training)\) and \(fb(testing)\). The set \(fa\), that is usually used as training set, contains 1204 (746+458) images of 403 male subjects and 403 female subjects. The set \(fb\), contains 1196 (740 male + 456 female) images which were taken seconds after the corresponding \(fa\) images but with different face expression, illumination and pose.

4. COMPARISION TO OTHER TECHNIQUES

In this paper proposed a novel approach for face recognition problem, and compared the different preprocessing methods and different feature extraction methods, meanwhile have shown the
performances of different combinations. One of the major sections of the project is compared proposed spatial WLD results with state-of-the-art best techniques: Multi-resolution Decision Fusion method, Local Gabor Binary Pattern with LDA and SVMAC method and Local Gabor Binary Pattern with LDA and SVM method. Also compared it with holistic WLD and PCA. Fig shows that despite being much simpler than other three methods, Spatial WLD gives comparable recognition rate and is much better than holistic WLD and PCA.

PCA based face recognition system is appropriate for both types of database.

5. IMPLEMENTATION

After faces are detected by face detection algorithm, they need to be decided his or her names. This is the task achieved by name identification based on face recognition. Similar to the face detection task, the name identification task is also considered as a binary classification problem and it will be done by recognizing the faces to identify the name though the database. Essentially, Name identification through face recognition consists of 4 main steps (1) Pre-processing, (2) Feature Detection, (3) Euclidean Distance and (4) Name Classification.

5.1 Pre-Processing

Since, in real-life, it is unlikely that people will face directly and frontally towards the camera, face images often consist of some in-plane and out-of-plane Rotations. Moreover, it is also unlikely that the light condition will be the same for all images. These variations greatly affect an accuracy of name classifiers. The purpose of pre-processing step is thus to remove these variations as much as possible. As with other computer vision applications, there is no unique solution to this problem. The common techniques involved in pre-processing step are face alignment, and light normalization. Face alignment tries to align faces such that they are closed to a common or specified pose of face as much as possible, whereas light normalization tries to get rid of the variation in illumination. One of the common employed normalization techniques in the name classification field is histogram equalization.

5.1.1 Normalization

Normalization is a process that changes the range of pixel intensity values. The linear normalization of a grey scale digital image is performed according to the formula. For example, if the intensity range of the image is 50 to 180 and the desired range is 0 to 255 the process entails subtracting 50 from each of pixel intensity, making the range 0 to 130. Then each pixel intensity is multiplied by 255/130, making the range 0 to 255.

\[ I_N = \left( \frac{I - \text{newMin}}{\text{Max} - \text{Min}} \right) \times \text{newMax} \] (10)

5.2 Feature Detection

Working directly on raw pixel values can be very slow as one small face image can contain a thousand of pixels. Furthermore, not all the pixels will be useful. There can be an underlying structure that describes the differences between male and female faces better. Thus the feature detection module is employed here.

5.3 Euclidean Distance

The Euclidean distance or Euclidean metric is the ordinary distance between two points that one would measure with a ruler, and is given by the Pythagorean formula. By using this formula as distance, Euclidean space (or even any inner product space) becomes a metric space. The associated norm is called the Euclidean norm. Older literature refers to the metric as Pythagorean metric.

Where, D - Database image, Ii - Input image

5.4 Name Classification

Generally there are two types of features presented in the name classification context, geometric-based features and appearance-based features. (a) Geometric-based features (also called local features) came from psychophysical explorations. They represent high-level face descriptions such as distances between nose, eyes and mouth, face width, face length, eyebrow thickness and so on. (b) Appearance-based features (also called global features) use low-level information about face image areas based on pixel values.

6. SIMULATION RESULTS & ANALYSIS

The forgeries were collected by forms with 15 boxes. Each forger form showed five images of different genuine signatures chosen randomly. The forger imitated each one three times for all five signatures. They were given unlimited time to learn the signatures and perform the forgeries. The forgers
are not experts. The complete signing process was supervised by an operator. The sheets were scanned at 600 dpi with 256 gray levels, automatically segmented and manually.

The accuracy of the result in the face recognition problem is improved by using WLD as a local descriptor that produces better result than other techniques. The best result is obtained when the standard block sizes and T, M, S are maintained. While using classifier like minimum distance and chi-square distance classifier, in spite of its simplicity the proposed system can produce improvement result of difficult systems.

Face identification is a technology just reaching sufficient maturity for it to experience a rapid growth in its practical applications. Much research effort around the world is being applied to expanding the accuracy and capabilities of this biometric domain, with a consequent broadening of its application in the near future. Verification systems for physical and electronic access security are available today, but the future holds the promise and the threat of passive customization and automated surveillance systems enabled by face recognition.

REFERENCES