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Block Based WLD: An Illumination Invariant Face Recognition Approach

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ABSTRACT: In many of the visual surveillance systems, face recognition plays an important role in providing biometric based security. In this paper, we present a method for face recognition which is based on Weber's principle. Unlike a global descriptor which is developed by the research community called Weber Local Descriptor (WLD) for texture recognition, we designed here a local descriptor based on Weber's law suitable to face recognition. It is well known in the image processing literature that the Weber local descriptor is one of the important dense descriptor which captures best texture details and possesses invariance to texture variations under varying lighting conditions. The WLD consists of two components: differential excitation and orientation. The differential excitation component is a function of the ratio between two terms: one is the relative intensity differences of a current pixel against its neighbours; the other is the intensity of the current pixel. The orientation component is the gradient orientation of the current pixel. It is observed that one of the major problems faced in the face recognition domain is the development of illumination invariant face recognition system. Hence in this work, we developed an illumination invariant face recognition approach using block based WLD. Here, we have extended WLD as block based WLD considering face recognition problem. We extend it by introducing local spatial information; divide a face into number of blocks. The WLD descriptor for each block is calculated and histogram for each block is concatenated. The developed block based WLD approach is tested considering several face datasets. In particular, experiments have been conducted on ORL, JAFFE, UMIST and IITK face datasets. From the experimental results, it is proved that the blockwise WLD method for face recognition is more accurate than the conventional WLD.

KEYWORDS: Weber's Principle, Local Descriptor, Face Recognition.

I. INTRODUCTION

The face is one of the well known biometric for automatically identifying or verifying a person from a digital image or a video frame of a video source [8]. One of the ways to achieve this is by comparing selected facial features from the image and a facial database i.e., biometric identification by scanning a person's face and matching it against a library of known face. There are number of applications where face recognition can play an important role including biometric authentication, visual surveillance and security systems, image retrieval and passive demographical data collections. It is observable that our behaviour and social interaction are by face recognition system [11] which could have great impact in improving human computer interaction systems in such a way so as to make them be more user-friendly and acting more human-like. It is unarguable that face is one of the most important features that characterize human beings.

Recently, there has been much interest in object and view matching using local invariant features [10], classification of textured regions using micro textons [6] and in face detection using local features [5]. These methods can be divided into two classes: one is a sparse descriptor which first detects the interest points in a given image, and then samples a local patch and describes its invariant features [17, 13]; the other is a dense descriptor, which extracts local features pixel by pixel over the input image [2, 4]. For the sparse descriptors, a typical one is the scale invariant feature transform (SIFT), introduced by Lowe [10]. It performs best in the context of matching and recognition due to its invariance to scaling and rotations [13]. Several attempts to improve the SIFT descriptor have been reported in the literature. Ke and Sukthankar developed the PCA-SIFT descriptor which represents local appearance by principal components of the normalized gradient field [9]. Mikolajczyk and Schmid modified the SIFT descriptor by changing the gradient location orientation grid, as well as the quantization parameters of the histograms [13]. Dalal and Triggs proposed a "histogram of oriented gradients" (HOG) [12]. Lazebnik et al. proposed a rotation invariant descriptor called the Rotation Invariant Feature Transform (RIFT) [7]. Bay et al. proposed an efficient implementation of SIFT by applying the integral image to compute image derivatives, and quantifying the gradient orientations in a small number

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of histogram bins [14]. Winder and Brown learned an optimal parameter setting on a large training set to maximize the matching performance [16]. Mikolajczyk and Matas developed the optimal linear projection to improve the matching quality and speed of SIFT [15]. Likewise, in order to improve the efficiency of the local descriptor, Tola et al. [19] replaced the weighted sum rule used in SIFT by sum of convolutions. Cheng et al. proposed the use of multiple support regions of different sizes surrounding a point of interest [18]. Among the most popular dense descriptors are the Gabor wavelet [3]. The Gabor representation has been shown to be optimal in the sense of minimizing the joint two-dimensional uncertainty in space and frequency. The Gabor filters can be considered as orientation and scale tunable edge and line (bar) detectors, and the statistics of these micro features in a given region are often used to characterize the underlying texture information. The Gabor wavelet has been widely used in image analysis applications, including texture classification and segmentation. Another one more important dense descriptor which is discussing here is Weber's Local Descriptor.

In this paper, we propose a simple, yet very powerful and robust local descriptor called WLD descriptor [20] which is based on Weber's Law. Weber's Law states that, the ratio of the increment threshold to the background intensity is a constant. This descriptor consists of two components: differential excitation and orientation. It is inspired by Weber's Law, which is a psychological law [1]. It states that the change of a stimulus (such as sound, lighting) that will be just noticeable is a constant ratio of the original stimulus. When the change is smaller than this constant ratio of the original stimulus, a human being would recognize it as a background noise rather than a valid signal. Motivated by this point, for a given pixel, the differential excitation component of the proposed Weber's Local Descriptor (WLD) is computed based on the ratio between the two terms: one is the relative intensity differences of a current pixel against its neighbors (e.g., 3×3 square region); the other is the intensity of the current pixel. With the differential excitation component, we attempt to extract the local salient patterns in the input image. In addition, we also compute the gradient orientation of the current pixel. That is, for each pixel of the input image, we compute two components of the WLD feature (i.e., differential excitation and gradient orientation). By combining the WLD feature per pixel, we represent an input image (or image region) with a histogram, which we call a WLD histogram hereinafter. In our case, the WLD feature is computed pixel wise. Thus, WLD is a dense descriptor. In our work, face area is first divided into small regions from which Weber's Local Descriptor (WLD) operator is computed. The computed WLD patterns are used to compute the histogram and concatenated into single spatial WLD histogram which represents the face image. Here in this features are extracted from each region. The recognition accuracy is estimated using Euclidean distance as a similarity measure. The rest of the paper is organized as follows. The details of WLD are presented in Section II, the blockwise based WLD is discussed in Section III. In Section IV, we present the experimental results and conclusions are given in Section V.

II. RELATED WORK

In this section, we review Weber's Law and then propose a block based descriptor using WLD principle.

A. *Weber's law*

Ernst Heinrich Weber, an experimental psychologist in 19th century, observed that the ratio of the increment threshold to the background intensity is a constant [20]. This relationship, known since as Weber's Law, can be expressed as:

Weber's Law, can be stated as:

$$\frac{\Delta I}{I} = K$$

where ΔI represents the increment threshold (just noticeable difference for discrimination); I represents the initial stimulus intensity and k signifies that the proportion on the left side of the equation remains constant despite of variations in the I term. The fraction $\Delta I/I$ is known as the Weber fraction.

B. *Weber's Local Descriptor (WLD)*

WLD consists of two components: differential excitation ($\mathcal{E}$) and orientation (θ). The differential excitation component is a function of the ratio between two terms: one is the relative intensity differences of a current pixel

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against its neighbors; the other is the intensity of the current pixel. And the orientation component is the gradient orientation of the current pixel.

C. Differential Excitation

One of the major components in WLD is differential excitation. The accuracy of the system depends on its parameter. Differential excitation is represents as $\mathcal{E}$ (x_c). Here in figure 1(a), we show central pixel and its neighborhood pixel under process to obtain differential excitation information.

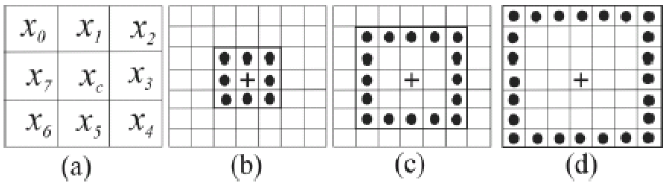

Fig.1(a). Central pixel and its neighbors' in case p = 8. (b) (8, 1) neighborhood of the central pixel, (c) and (d) (16,2 (27, 3), respectively, neighborhood's of the central pixel.

For calculating differential excitation $\mathcal{E}$ (x_c) of a pixel X_c, first intensity differences of X_c with its neighbor's x_i, i = 0, 1, 2… p-1 (see Figure 1(b) for the case p = 8) are calculated as follows:

$$\Delta I_i = I_i - I_c \qquad (1)$$

Then the ratio of the total intensity difference of x_c with its neighbours x_i to the intensity of x_c is determined as follows,

$$f_{ratio} = \sum_{i=0}^{p-1}\left(\frac{\Delta I_i}{I_c}\right) \qquad (2)$$

Arctangent function is used as a filter on *Eq* (2) to enhance the robustness of WLD against noise which results in:

$$\varepsilon(x_c) = arctan\left[\sum_{i=0}^{p-1}\left(\frac{\Delta I_i}{I_c}\right)\right] \qquad (3)$$

The differential excitation ε(x_c) may be positive or 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.

D. Gradient Orientation

Next main component of WLD is gradient orientation. For a pixel the gradient orientation is calculated as follows:

$$\theta(x_c) = arctan\left[\frac{I_{73}}{I_{51}}\right] \qquad (4)$$

Where $I_{73} = I_7 - I_3$ is the intensity difference of two pixels on the left and right of the current pixel x_c, and $I_{51} = I_5 - I_1$ is the intensity difference of two pixels directly below and above the current pixel ,$\theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$.

The gradient orientations are quantized into T dominant orientations as:

$$\emptyset_t = \frac{2t}{T}\pi \text{ where } t = mod\left(\left\lfloor\frac{\theta'}{2\pi/T} + \frac{1}{2}, T\right\rfloor\right) \qquad (5)$$

Where $\theta' \in [0, 2\pi]$ and is defined in terms of gradient orientation computed by Eq. (4) as,

$$\theta' = arctan2(I_{73}, I_{51}) + \pi$$

In case, the dominant orientations are $\emptyset_t = \frac{t\pi}{4}$, t=0,1,..,T-1; all orientations located in the interval $[\emptyset_t - (\frac{t\pi}{4}), \emptyset_t + (\frac{t\pi}{4})]$ are quantized as ϕ_t .

From this, both differential excitation ε(x_c) and gradient orientation (θ) are combined to compute the WLD histogram and concatenate into single spatial WLD histogram, which represents the face image. In this way, features

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are extracted from each region. The recognition accuracy is estimated using Euclidean distance as a similarity measure. Experiments conducted for various standard dataset like ORL, JAFFE, IITK and UMIST face datasets. It is observed from the literature that the local feature extraction methods exhibit better performance when compared to the global feature extraction methods. Hence we made the existing WLD as local feature extraction method. In our work we partition the image into set of sub images and WLD is employed on each sub image. The details of this methodology are given in the following section.

III. BLOCKWISE WEBER LOCAL DESCRIPTOR BASED FACE RECOGNITION

The blockwise Weber's Local Descriptor is proposed to which is found to be more accurate when compared to conventional global WLD. In figure 2, we have shown how original image is divided into 4 blocks. Here image can divided into four and sixteen blocks and for each block compute WLD histogram and concatenate into single spatial WLD histogram, by this features are extracted from each region which represents the whole face image. The feature extraction approach will be used for both test and train database images to recognize face. The face will be recognized by finding Euclidean distance between them.

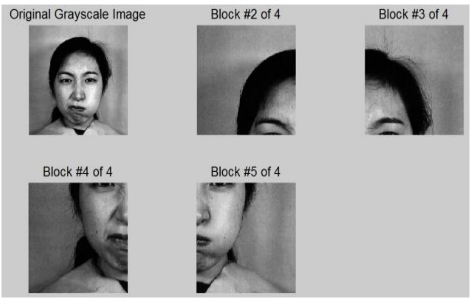

Fig.2. Original image is divided into four blocks

IV. EXPERIMENTAL RESULTS

The blockwise WLD is applied on ORL, JAFFE, IITK, and UMIST databases and recognition rates are calculated and compared between WLD and Block based WLD. From the comparison between the recognition rate of WLD and Blockwise WLD, it is clear that the four blocks are sufficient and recognition accuracy is reasonably efficient than the basic WLD and the sixteen blocks is much more efficient than basic WLD method. If we increase more than sixteen blocks, less feature will be extracted and this leads to less recognition rate. Hence four and sixteen blocks are sufficient for good recognition rate.

A. Experimental Results on ORL Database

The ORL database consist of 40 persons images. There are 10 samples of each person's image. These 10 samples represent different variations in expressions, facial details and limited rotations as shown in fig 3. Each image is cropped to the size of 112×92 pixels. After computing WLD and Block based WLD for ORL database, the experimental results exhibit that the recognition rate on Blockwise WLD is better than the global WLD as shown in Table 1.

Fig. 3. Images of ORL database.

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(An ISO 3297: 2007 Certified Organization)

Vol. 3, Special Issue 7, October 2015

B. Experimental Results on JAFFE Database

JAFFE database consist of 20 persons images. There are 10 samples of each person's image. There are total 200 images considered for the experiment. Fig 4 shows that each image is cropped to the size of 112×92 pixel. Table 3 gives the recognition rate on Blockwise WLD which is better than the global WLD.

Fig.4. Images of JAFFE database

C. Experimental Results on IITK Database

IITK database consists of 32 persons color images. There are 12 samples for each person. These twelve samples are varying in pose, expressions. Each color image is converted into gray image of size 100×100 pixels. Fig 5 shows the sample images on IITK database. After computing WLD and Block based WLD for JAFFE database, the experimental results exhibit that the recognition rate on Blockwise WLD is better than the global WLD as shown in Table 4.

Fig.5. Images of IITK database

D. Experimental Results on UMIST Database

UMIST database consist of 560 images of 20 persons. Only 19 views of 20 person's images are considered for the experiment. Each image is cropped to the size of 112×92 pixels as shown in fig 6. Table 2 gives the recognition rate on Blockwise WLD which is found to be better than the global WLD.

Fig.6. Images of UMIST database

In all the below shown tables, different sets of training images and testing images are considered. From the tables, it is clear that the recognition rate increases by increasing the number of blocks. The recognition rate of blockwise WLD is greater than the global WLD.

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Table 1. Recognition rate comparison between WLD and blockwise WLD for ORL database

ORL DATABASE			RECOGNITION RATE (%)		
Sl.No	TRAINING IMAGES	TESTING IMAGES	WLD	BLOCKWISE WLD(4BLOCKS)	BLOCKWISE WLD(16BLOCKS)
1	1,2,3,4,5	6,7,8,9,10	76%	90.5%	95.5%
2	1,3,5,7,9	2,4,6,8,10	84%	92%	95%
3	2,4,6,8,10	1,3,5,7,9	82%	93.5%	96%
4	1,2,3	4,5,6,7,8,9,10	64%	78%	87.85%
5	5,6,7,8,9,10	1,2,3,4	66%	80.4%	88%

Table 2. Recognition rate comparison between WLD and blockwise WLD for UMIST database

UMIST DATABASE			RECOGNITION RATE (%)		
Sl. No	TRAINING IMAGES	TESTING IMAGES	WLD	BLOCKWISE WLD(4BLOCKS)	BLOCKWISE WLD(16BLOCKS)
1	1,2,3,4,5,6,7,8	9,10,11,12,13,14,15,16	51%	67%	68%
2	2,4,6,8,10,12,14,16	1,3,5,7,9,11,13,15	96%	99%	100%
3	1,3,5,7,9,11,13,15	2,4,6,8,10,12,14,16	96%	99%	100%
4	1,4,7,10,13,16,19	2,5,8,11,14,17	85%	87%	90%
5	1,2,3,4	5,6,7,8,9,10,11,12,13, 14,15,16	35%	55%	55%

Table 3. Recognition rate comparison between WLD and blockwise WLD for JAFEE database

JAFFE DATABASE			RECOGNITION RATE (%)		
Sl. No	TRAINING IMAGES	TESTING IMAGES	WLD	BLOCKWISE WLD(4 BLOCKS)	BLOCKWISE WLD(16 BLOCKS)
1	1,2,3,4,5,6,7,8,9,10	11,12,13,14,15,16,17,18,19,20	64%	68%	70%
2	1,3,5,7,9,11,13,15,17,19	2,4,6,8,10,12,14,16,18,20	89%	91%	93%
3	2,4,6,8,10,15,14,16,18,20	1,3,5,7,9,11,13,15,17,19	87.14%	92%	93%
4	1,2,3,4,5	6,7,8,9,10,11,12,13,14,15, 16,17,18,19,20	56%	60%	61%
5	1,4,7,10,13,15,19	2,5,8,11,14,17,20	84%	88%	88%

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Table 4. Recognition rate comparison between WLD and blockwise WLD for IITK database

IITK DATABASE			RECOGNITION RATE (%)		
Sl.No	TRAINING IMAGES	TESTING IMAGES	WLD	BLOCKWISE WLD(4BLOCKS)	BLOCKWISE WLD(16BLOCKS)
1	1,2,3,4,5,6	7,8,9,10,11,12	45%	56%	57%
2	1,3,5,7,9,11	2,4,6,8,10,12	47%	57%	63%
3	2,4,6,8,10,12	1,3,5,7,9,11	51%	60%	69%
4	1,4,7,10	2,5,8,11	43%	51%	53%
5	1,2,3,4,5,6,7,8,	8,9,10,11,12	46%	53%	55%

V. CONCLUSION

In this paper, we have presented a block based WLD for face recognition). It is based on the fact that human perception of a pattern depends not only on the change of a stimulus (such as sound, lighting) but also on the original intensity of the stimulus. Experiments are conducted on ORL, IITK, JAFFE and UMIST database. It is concluded from our experimental results that the Block based WLD is much better than the global WLD for face recognition problem. Our future interest lies in how to exploit the proposed descriptor for the domain of matching sketch images with the digital face images.

REFERENCES

[1]. A. K. Jain. Fundamentals of Digital Signal Processing. Englewood Cliffs, NJ: Prentice-Hall, 1989
[2]. T. Ojala, M. Pietikäinen and D. Harwood, “A Comparative Study of Texture Measures with Classification Based on Feature Distributions,” Pattern Recognition, vol. 29, no. 1, pp. 51-59, 1996.
[3]. B. Manjunath and W. Ma, “Texture Features for Browsing and Retrieval of Image Data,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 18, no. 8, pp. 837-842, 1996.
[4]. T. Randen and J.H. Husoy, “Filtering For Texture Classification: A Comparative Study,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 21, no. 4, pp. 291 - 310,1999.
[5]. P. Viola and M. Jones, “Rapid Object Detection Using a Boosted Cascade of Simple Features,” Proc. IEEE Int’l Conf. on Computer Vision and Pattern Recognition, 2001.
[6]. T. Ojala, M. Pietikäinen and T. Mäenpää, “Multiresolution Gray Scale and Rotation Invariant Texture Analysis with Local Binary Patterns,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971 - 987, 2002.
[7]. S. Lazebnik, C. Schmid and J. Ponce, “A Sparse Texture Representation Using Local Affine Regions,” Proc. IEEE Int’l Conf. on Computer Vision and Pattern Recognition, 2003.
[8]. Jain A.K, A.Rose, and S. Prabhakar. “An introduction to Biometric Recognition”, IEEE TCSVT, vol.14 (1), pp.4-20, 2004.
[9]. Y. Ke and R. Sukthankar, “PCA-SIFT: A More Distinctive Representation for Local Image Descriptors,” Proc. IEEE Int’l Conf. on Computer Vision and Pattern Recognition, 2004.
[10]. D. Lowe, “Distinctive Image Features from Scale Invariant Key Points,” International Journal of Computer Vision, vol. 60, no. 2, pp. 91110, 2004.
[11]. V. Bruni and D. Vitulano. A Generalized Model for Scratch Detection, IEEE TIP, 2004
[12]. N. Dalal and B. Triggs, “Histograms of Oriented Gradients for Human Detection,” Proc. IEEE Int’l Conf. on Computer Vision and Pattern Recognition, 2005.
[13]. K. Mikolajczyk and C. Schmid, “A Performance Evaluation of Local Descriptors,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 27, no. 10, pp. 1615-1630, 2005.
[14]. H. Bay, T. Tuytelaars and L. van Gool. “SURF: Speeded Up Robust Features,” Proc. European Conf. on Computer Vision, 2006.
[15]. K. Mikolajczyk and J. Matas, “Improving Descriptors for Fast Tree Matching by Optimal Linear Projection,” Proc. IEEE Int’l Conf. on Computer Vision, 2007.
[16]. S. Winder and M. Brown, “Learning Local Image Descriptors,” Proc. IEEE Int’l Conf. on Computer Vision and Pattern Recognition, 2007.
[17]. P. Moreels and P. Perona, “Evaluation of Features Detectors and Descriptors based on 3D objects,” International Journal of Computer Vision, vol. 73, no. 3, pp. 263-28, 2007.
[18]. H. Cheng, Z. Liu N. Zheng and J. Yang, “A Deformable Local Image Descriptor,” Proc. IEEE Int’l Conf. on Computer Vision and Pattern Recognition, 2008.

[19]. E. Tola, V. Lepetit and P. Fua, "A Fast Local Descriptor for Dense Matching," Proc. IEEE Int'l Conf. on Computer Vision and Pattern Recognition, 2008.

[20]. Jie Chen, Shiguang Shan, Chu He, Guoying Zhao, Matti Pietikainen, Xilin Chen, and Wen Gao, *"WLD: A Robust Local Image Descriptor"*, IEEE Transactions On Pattern Analysis And Machine Intelligence, Vol. 32, No. 9, September 2010

[21]. Ihsan Ullah, Muhammad Hussain, Ghulam Muhammad, Hatim Aboalsamh, George Bebis and Anwar M. Mirza, "Gender Recognition From Face Images With Local WLD Descriptor", IWSSIP 2012, 11-13 April 2012, Vienna, Austria.

[22]. Shardool. V. Patil, M. M. Sardeshmukh, "Face Recognition by Weber Law Descriptor for Anti-Theft Smart Car Security System", International Journal of Emerging Technology and Advanced Engineering Website: www.ijetae.com (ISSN 2250-2459, ISO 9001:2008 Certified Journal, Volume 4, Issue 5, May 2014).

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