The Variants of Weber Local Descriptor and Their Applications for Biometrics

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Abstract. In computer vision and pattern recognition, handcrafted local features play an important role in many tasks. Many effective handcrafted local features have been proposed. Among them, Weber Local Descriptor (WLD) is a successful one. WLD is a simple but powerful descriptor, and a lot of variants of WLD have also been proposed in recent years, which has been broadly used for texture classification as well as biometrics. In this paper, we make a review for WLD and its variants. Generally, the algorithms of WLD and its variants can be divided into categories such as differential excitation-based, orientation-based and multiple features based. We also summarize their applications for biometrics.

Keywords: Weber local descriptors · Survey · Biometrics

1 Introduction

In computer vision and pattern recognition, image local descriptors play an important role for many recognition tasks. A lot of local descriptors have been proposed in the past decade such as Scale-Invariant Feature Transform (SIFT), Local Binary Pattern (LBP), Histogram of Oriented Gradient (HOG), and Weber Local Descriptor (WLD), etc. Among them, WLD is a new one proposed by Chen et al. [1] in 2010. In WLD, differential excitation and orientation of the input image are firstly calculated, and then the histogram is constructed according to these two components. Generally, WLD descriptor has the following advantages: (1) It utilizes Weber function to detect local salient pattern which make it more robust to noises and illumination changes. (2) It constructs histogram according to salient pattern's gradient orientation, combining two features together make it more discriminatory. After WLD descriptor was proposed, a lot of its variants have been proposed and have achieved very promising performance for different tasks. In this paper, we make a review for WLD and its variants. We firstly

present the basic algorithm of WLD. Secondly, we divide the algorithms of WLD's variants into three categories such as differential excitation-based, orientation-based and multiple features based. Finally, we summarize their applications for biometrics.

2   Basic Algorithm of Weber Local Descriptor

2.1   Weber's Law and Differential Excitation Descriptor

In the fields of psychology, Weber's law holds that the ratio of stimulation increment ΔI to its original intensity I is a constant. It means we have reason to think that the region is background or area containing noises if the region changes after stimulation. Inspired by Weber's Law, Chen et al. [1] proposed differential excitation descriptor to calculate such a change:

$$\xi(x_c) = arctan\left(\frac{v_s^{00}}{v_s^{01}}\right) = arctan\left[\sum_{i=0}^{p-1}\left(\frac{x_i - x_c}{x_c}\right)\right] \tag{1}$$

where p is the number of neighboring pixels, x_c is the central pixel and x_i indicates the ith neighboring pixel, v_s^{00} and v_s^{01} are calculated through two differential excitation masks f_{00} and f_{01} as shown in Fig. 1.
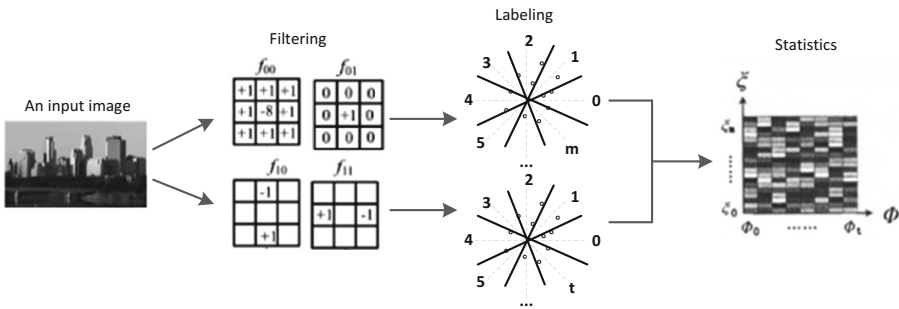

Fig. 1. The construction process of Weber local descriptor.

2.2   Orientation and Histogram

The orientation component of WLD is gradient orientation of current pixel:

$$\theta(x_c) = arctan\left(\frac{x_5 - x_1}{x_7 - x_3}\right) \tag{2}$$

where $x_5 - x_1$ and $x_7 - x_3$ are the intensity differences in vertical and horizontal direction. After calculating these two components, a 2-dimensional histogram $\{WLD(\xi_j, \phi_t)\}$ is constructed for feature representation. For simplicity, this 2D

histogram is further encoded into 1D histogram according to each column. Such a WLD feature has been successfully used in texture classification and face recognition [1].

3   The Variants of WLD Descriptor

A lot of variants of WLD have been proposed, which can be classified into three types *i.e.*, differential excitation-based, orientation-based and multiple features-based. Table 1 lists 13 variants of WLD, and these variants will be introduced in our paper one by one.

Table 1. The variants of WLD

Category		Method name	Main changes	Applications	Year
Differential Excitation-based	(1)	MWLD_1 [2]	Template's weights	Space image registration	2010
	(2)	SWLD [3]	Neighboring pixels' numbers	Cross spectral face recognition	2012
	(3)	GWLD [4]	Applying on Gabor magnitude map	Bovine iris recognition	2013
	(4)	IWLD [5]	Considering angles between intensity differences and X direction	Violence detection	2016
Orientation-based	(5)	WLD [6]	Using Sobel operator	Face recognition	2011
	(6)	MWLD_2 [7]	Using orientation component as histogram's weights	Pedestrian detection	2011
	(7)	CHILD [8]	Filtering method modified	Texture classification	2013
	(8)	WOD [9]	Using positive differential excitation and Gabor filters for orientation	Vanishing point detection	2014
	(9)	IWLD [10]	Coding with local binary patterns	Person re-identification	2015
Multiple Features-based	(10)	LBP/WLD [11]	Using LBP for differential excitation	Dynamic texture recognition	2011
	(11)	WLDV [12]	Adding contrast information	Texture classification	2012
	(12)	PWMO [13, 14]	Using p-LBP and local XOR pattern	Face recognition	2012
	(13)	WLBP [15]	Combining LBP with WLD	Face recognition	2013

3.1   Differential Excitation-Based Variants of WLD

The differential excitation component of WLD aims to extract local salient patterns, so it is necessary for this component to be expressive and robust. According to this principle, several variants of WLD have been proposed.

(1) Modified WLD (MWLD)
Jiao and Baojun [2] proposed MWLD for space image registration. The modules of differential excitation and orientation are modified to fit the circle stars' smooth edges and to extract more sharp edge information. Those modules are showed in Fig. 2. Experiments show it is expressive for space images.

+1	+2	+1	0	+2	0	0	+1	0	0	0	0
+1	−8	+1	+1	−5	+1	0	−3	0	+1	−3	−1
+1	+2	+1	0	+2	0	0	−1	0	0	0	0

$$m_{00} \qquad\qquad m_{01} \qquad\qquad m_{10} \qquad\qquad m_{11}$$

Fig. 2. Modules of differential excitation and orientation in MWLD

(2) Simplified WLD (SWLD)
Zuo *et al.* [3] proposed a methodology for face images called SWLD, which is applied on the magnitude of Gabor filtered image and only computes differential excitation around current pixel's 12 neighbors:

$$SWLD_{l,r,12}(x) = \vartheta_l\left\{ tan^{-1}\left[\sum\nolimits_{i=0}^{11} \frac{x_i - x}{x}\right]\right\} \tag{3}$$

where x_i are 12 neighbors of x at radius r and ϑ_l is a uniform quantizer with l quantization levels. After calculating SWLD and LBP on magnitude of filtered image and GLBP on phase of filtered image, concatenated histogram is built and successfully used for face recognition.

(3) Gabor WLD (GWLD)
Motivated by WLD and the advantages of Gabor, Sun *et al.* [4] proposed GWLD for bovine iris recognition. The original images are preprocessed with a set of Gabor filters to obtain 40 magnitude maps. Then a modified WLD [16] is applied over each map. It calculates differential excitation with the largest intensity difference in the neighborhood:

$$\xi(x_c) = arctan\left[\frac{f_{00}}{x_c}\right], f_{00} = p * (x_j - x_c) \tag{4}$$

where x_j is the corresponding neighbor pixel of Chebyshev distance:

$$x_j = argmax_{x_i}|x_i - x_c|, i = 0, 1, \ldots, p - 1 \tag{5}$$

Orientation is the same as original WLD's gradient orientation. Finally, GWLD histogram is obtained and experiments show it has encouraging performance, but with high computation cost.

(4) Improved WLD (IWLD)

Since WLD is not good at handling information of flat area, Zhang *et al*. [5] proposed IWLD, which computes the orientation of eight intensity differences separately:

$$\xi_{mx}(x_c) = arctan(\alpha\langle X, J_x\rangle), \xi_{my}(x_c) = arctan(\alpha\langle X, J_y\rangle) \tag{6}$$

where $X = \left(\frac{x_0-x_c}{x_c}, \frac{x_1-x_c}{x_c}, \ldots, \frac{x_{p-1}-x_c}{x_c}\right)^T$ and $\langle,\rangle$ is the inner product operator. $J_x = \left(cos\theta_0, cos\theta_1, \ldots, cos\theta_{p-1}\right)^T$ and $J_y = \left(sin\theta_0, sin\theta_1, \ldots, sin\theta_{p-1}\right)^T$ denote the angle between X direction and $x_i - x_c$.

Then, IWLD magnitude and orientation are defined according to those two values:

$$\xi_m(x_c) = \sqrt{(\xi_{mx}(x_c))^2 + (\xi_{my}(x_c))^2}, \xi_o(x_c) = arctan\frac{\xi_{my}(x_c)}{\xi_{mx}(x_c)} \tag{7}$$

Angle information of each neighboring pixel's intensity difference makes contributions to image representation. Experiments on face databases demonstrate the proposed approach's excellent performance.

3.2 Orientation-Based Variants of WLD

Since direction information makes great contributions for some recognition tasks, several orientation-based variants of WLD have also been proposed.

(5) Sobel WLD

Original WLD's gradient orientation considers only vertical and horizontal neighboring pixels, which is susceptible to noises. It has been replaced with Sobel operator [6, 17] and Isotropic Sobel operator [18], which calculates six neighboring pixels instead of four neighboring pixels. Experiments show it can provide more stable feature histograms and enhance the classification rates for face recognition.

(6) Modified WLD (MWLD)

Lian *et al*. [7] proposed MWLD as the pedestrian detector. The novelty is that the histogram is constructed in a new way by voting the gradient magnitude into each bin:

$$MWLD_{2D}(r, t) = \sum_{i=0}^{M-1}\sum_{j=0}^{N-1} \omega(x_{i,j})\varphi(\xi(x_{i,j}), r)\varphi(\theta(x_{i,j}), t) \tag{8}$$

and

$$\omega(x_{i,j}) = \sqrt{(x_5 - x_1)^2 + (x_7 - x_3)^2}, \varphi(x, y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \tag{9}$$

where M*N represents the image size, r and t are the numbers of the differential excitation bins and dominant orientation. Experiments on fast pedestrian detection show MWLD performs better than other descriptors with higher speed.

(7) Computationally-Efficient Histogram-Based Image Local Descriptor (CHILD)

In order to solve the problem of sensitiveness to noise and image rotation, Anamandra and Chandrasekaran [8] proposed a descriptor called CHILD, which uses Laplacian of Gaussian for differential excitation, and the orientation is obtained by convolving with Tiansi fractional derivative filter. CHILD histogram is constructed at last, which seems more robust for texture classification. It has also been used on color texture images in [19].

(8) Weber Orientation Descriptor (WOD)

Weibin *et al.* [9] designed WOD for vanishing point detection. The differential excitation considers positive value of average differences:

$$\xi_{WOD}(p_c) = \begin{cases} \sqrt{G(p_c)}, & if \ G(p_c) \geq 0 \\ 0, & if \ G(p_c) < 0 \end{cases}, \ G(p_c) = arctan\left(\frac{p_c - \bar{p}_i}{p_c}\right) \qquad (10)$$

The orientation is computed as the index of maximum Gabor energy:

$$\theta_{WOD}(p_c) = Argmax_{\varphi_n} E_{\varphi_n}(p_c), E_{\varphi_n}(p_c) = Re\left(\hat{I}_{\varphi_n}(p_c)\right)^2 + Im\left(\hat{I}_{\varphi_n}(p_c)\right)^2 \qquad (11)$$

where $\hat{I}_{\varphi_n}(p_c)$ is the convolution of image and Gabor filter g_{φ_n}. Experiments show WOD can achieve favorable performance results.

(9) Improved WLD (IWLD)

After WLD, Chen et al. [10] proposed a new WLD for person re-identification. The orientation component is improved by coding LBP [20] after quantifying gradient orientation into several intervals:

$$LBP_{m,n}(x_c) = \left\lfloor B^p_{m,n}, B^{p-1}_{m,n}, \ldots, B^1_{m,n} \right\rfloor, B^i_{m,n} = q\left(\phi_{m,n}(x_c)\right) \otimes q\left(\phi_{m,n}(x_i)\right) \qquad (12)$$

where $\phi_{m,n}(x_c)$ is the value of orientation and $q(\cdot)$ is the floor function. Then the histogram is constructed according to the bins of differential excitation and orientation. Experimental results proved that the method is robust for image rotation and illumination, it performs well for person re-identification.

3.3   Multiple Features-Combined Variants of WLD

In order to extract richer information for recognition, researchers proposed several variants that combining other descriptors with WLD. In this section, we will briefly introduce these algorithms.

(10) LBP/WLD

Since LBP can capture the orientation of local textures, Yuqing and Yan [11] combined LBP and WLD into dynamic texture representation to achieve better performance.

WLD is computed with the sigmoid function of differential excitation, then the block match information is measured according to their LBP and WLD patterns:

$$(LBP/WLD)_m = \{i|min(Diff(p_0 - p_i))\} \tag{13}$$

where $Diff(\cdot)$ and WLD are defined as:

$$\text{Diff}(p_0 - p_i) = |LBP(p_0) - LBP(p_i)| + |WLD(p_0) - WLD(p_i)| \tag{14}$$

$$\text{WLD}(I_c) = sigmoid\left(\sum_{i=0}^{p-1} \left|\frac{I_i - I_c}{I_c}\right|\right) \tag{15}$$

At last, LBP/WLD histogram is concatenated with dynamic texture histogram. Experiments show it performances better than LBMP for dynamic texture recognition.

(11) WLD Variance (WLDV)
In order to improve texture classification accuracy, Dawood et al. [12] proposed a hybrid approach that combines WLD with contrast information, which is actually image variance calculated with the Probability Weighted Moments:

$$S_p = \frac{\sqrt{\pi}}{n} \sum_{i=0}^{n} \left[X_i - 2\left(1 - \frac{i - 0.5}{n}\right)X_i\right] \tag{16}$$

where X_i indicates ordered observations in a sample of size n. Finally, the joint histogram is represented for texture classification.

(12) Patterns of Weber Magnitude and Orientation (PWMO)
Wang et al. [13, 14] proposed a computationally efficient, discriminative and robust feature descriptor called PWMO for face recognition system. PWMO consist of two parts: patterns of Weber magnitude, which is encoded with patch-based LBP, and patterns of Weber orientation, which is encoded with patch-based local XOR:

$$\text{p\_LBP}(x_c, y_c) = \left[\sum_{n=0}^{7} 2^n D\left(S_1\left(P_{c_n^R}^r\right), S_1\left(P_c^r\right)\right), \ldots, \sum_{n=0}^{7} 2^n D\left(S_q\left(P_{c_n^R}^r\right), S_q\left(P_c^r\right)\right)\right] \tag{17}$$

where P_c^r is the image patch centered at current pixel with radius r, and c_n^R are the neighboring pixels with radius R. $S\left(P_c^r\right)$ is a pre-defined statistic such as the bins of magnitude histogram and the orientation with largest accumulative magnitude.

Finally, the concatenated histogram is constructed and block-based whitened PCA is introduced to select the most discriminative features. Experimental results demonstrate the proposed method is suitable for face recognition.

(13) Weber Local Binary Pattern (WLBP)
Liu et al. [15] proposed a local descriptor called WLBP, which uses Laplacian of Gaussian for differential excitation and uniform pattern of LBP [21] for orientation component. At last, a more discriminative and robust histogram is constructed. Experiments show it is superior to other state-of-the-art methods not only for face recognition, but also for texture classification.

4   Applications for Biometrics

After WLD has been proposed, it has been widely used on many applications. As for biometrics, WLD and its variants have been successfully applied on face detection [1], face recognition [14, 15], fingerprint liveness detection [22], iris recognition [4] and palmprint recognition [23]. WLD feature is robust to variations in facial expression and illumination, which make it performance well for face images. Since WLD is suitable for high-contrast patterns such as the ridges and valleys of fingerprint and palmprint, it achieves greater performance while using for the liveness detection on those two tasks. Besides, WLD also has been extended to bovine iris recognition, which is robust to noise and illumination in the original images, and it indeed has enhanced the representation power.

5   Conclusions

WLD has become one of important local image descriptors. In this paper, it is the first time to make a review of WLD and its variants. We also survey their applications for biometrics. After an analysis, we divide its variants into three categories, *i.e.,* differential excitation-based, orientation-based, and multiple features-based. For differential excitation-based methods, different differential excitation information is added to make the descriptor more robust to noise. For orientation-based methods, direction extraction algorithms are modified to obtain more effective feature representation. For multiple features based methods, WLD is combined with other descriptors to form a new descriptor and can capture richer information. In our future work, we plan to make a performance evaluation of WLD and its variants for different biometrics tasks such as face, iris, palmprint, and vein recognition.

References

1. Chen, J., Shan, S., He, C., Zhao, G., Pietikainen, M., Chen, X., Gao, W.: WLD: a robust local image descriptor. IEEE Trans. Pattern Anal. Mach. Intell. **32**(9), 1705–1720 (2010)
2. Jiao, J., Baojun, Z.: A new feature descriptor and selection method to space image registration. In: 2010 International Conference on Image Analysis and Signal Processing, 9–11 April 2010, pp. 314–317 (2010)
3. Zuo, J., Nicolo, F., Schmid, N.A., Boothapati, S.: Encoding, matching and score normalization for cross spectral face recognition: matching SWIR versus visible data. In: 2012 IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS), 23–27 September 2012, pp. 203–208 (2012)
4. Sun, S., Zhao, L., Yang, S., Sun, S., Zhao, L., Yang, S.: Gabor Weber local descriptor for bovine iris recognition. Math. Prob. Eng. **2013**(2), 1–7 (2013)
5. Zhang, T., Jia, W., He, X., Yang, J.: Discriminative dictionary learning with motion Weber local descriptor for violence detection. IEEE Trans. Circ. Syst. Video Technol. **27**(3), 696–709 (2016)

6. Dayi, G., Shutao, L., Yin, X.: Face recognition using the Weber local descriptor. In: The First Asian Conference on Pattern Recognition, 28 November 2011, pp. 589–592 (2011)

7. Lian, G., Lai, J., Yuan, Y.: Fast pedestrian detection using a modified WLD detector in salient region. In: Proceedings 2011 International Conference on System Science and Engineering, 8–10 June 2011, pp. 564–569 (2011)

8. Anamandra, S.H., Chandrasekaran, V.: CHILD: a robust computationally-efficient histogram-based image local descriptor. In: 2013 Fourth National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG), 18–21 December 2013, pp. 1–5 (2013)

9. Weibin, Y., Xiaosong, L., Bin, F., Daiming, Z., Yuan Yan, T.: Fast and accurate vanishing point detection in complex scenes. In: 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), 8–11 October 2014, pp. 93–98 (2014)

10. Chen, L., Chen, H., Li, S., Zhu, J.: Person re-identification by Weber local descriptors and color features. In: International Computer Conference on Wavelet Active Media Technology and Information Processing, pp. 273–278 (2015)

11. Yuqing, Q., Yan, T.: Dynamic texture recognition based on multiple statistical features with LBP/WLD. In: Proceedings of 2011 International Conference on Computer Science and Network Technology, 24–26 December 2011, pp. 957–960 (2011)

12. Dawood, H., Dawood, H., Guo, P.: Combining the contrast information with WLD for texture classification. In: 2012 IEEE International Conference on Computer Science and Automation Engineering (CSAE), 25–27 May 2012, pp. 203–207 (2012)

13. Wang, B., Li, W., Li, Z., Liao, Q.: Patterns of Weber magnitude and orientation for face recognition. In: IEEE International Conference on Image Processing, pp. 1441–1444 (2012)

14. Jiang, Y., Wang, B., Zhou, Y., Li, W., Liao, Q.: Patterns of Weber magnitude and orientation for uncontrolled face representation and recognition ✩. Neurocomputing **165**, 190–201 (2015)

15. Liu, F., Tang, Z., Tang, J.: WLBP: Weber local binary pattern for local image description. Neurocomputing **120**(10), 325–335 (2013)

16. Sun, S., Zhao, L.: Efficient modified Weber local descriptor approach to bovine iris recognition. ICIC Exp. Lett. Part B Appl. Int. J. Res. Surv. **3**, 1311–1317 (2012)

17. Li, S., Gong, D., Yuan, Y.: Face recognition using Weber local descriptors. Neurocomputing **122**, 272–283 (2013)

18. Zhang, X., Yang, J., Dong, S., Wang, C., Chen, Y., Wu, C.: Thermal infrared face recognition based on the modified blood perfusion model and improved Weber local descriptor. In: Sun, Z., Shan, S., Sang, H., Zhou, J., Wang, Y., Yuan, W. (eds.) CCBR 2014. LNCS, vol. 8833, pp. 103–110. Springer, Cham (2014). doi:10.1007/978-3-319-12484-1_11

19. Anamandra, S.H., Chandrasekaran, V.: COLOR CHILD: a novel color image local descriptor for texture classification and segmentation. Pattern Anal. Appl. **19**(3), 821–837 (2016)

20. Davarpanah, S.H., Khalid, F., Abdullah, L.N., Golchin, M.: A texture descriptor: BackGround Local Binary Pattern (BGLBP). Multimedia Tools Appl. **75**(11), 1–20 (2016)

21. Ojala, T., Pietikäinen, M., Mäenpää, T.: Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Anal. Mach. Intell. **24**(7), 971–987 (2000)

22. Gragnaniello, D., Poggi, G., Sansone, C., Verdoliva, L.: Fingerprint liveness detection based on Weber local image descriptor. In: 2013 IEEE Workshop on Biometric Measurements and Systems for Security and Medical Applications (BIOMS), pp. 46–50 (2013)

23. Aishwarya, D., Gowri, M., Saranya, R.K.: Palm print recognition using liveness detection technique. In: 2016 Second International Conference on Science Technology Engineering and Management (ICONSTEM), 30–31 March 2016, pp. 109–114 (2016)