Wavelet Transform based Score Fusion for Face Recognition using SIFT Descriptors

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Abstract: One of the main areas in computer vision is automatic face recognition which deals with detecting human face autonomously. Developments and the progress in the field of face recognition have shown that many face recognition systems and applications the automated methods outperform humans. The conventional Scale-Invariant Feature Transform (SIFT) is used in face recognition where they provide high performances. However, this performance can be improved further by transforming the input into different domains before applying SIFT algorithm. Hence, we apply Discrete Wavelet Transform (DWT) or Gabor Wavelet Transform (GWT) at the input face images, which provides denser and extra information to be used by the conventional SIFT algorithm. Matching scores of SIFT from each subimage is fused before making final decision. Simulations show that the proposed approaches based on wavelet transforms using SIFT provides very high performance compared to the conventional algorithm.

Keywords*:* SIFT, Face Recognition, Wavelet Transform, DWT, GWT, Score Fusion

1. Introduction

Face recognition is one of the most common biometric systems. Due to its higher acceptability rate, researchers have developed various algorithms for face recognition purpose. The process of recognition using these algorithms has been described as a difficult task because of the similarity nature or shapes of human faces (Betta et al., 2011). Despite the difficulties encountered in designing these systems, several reasons contributed to the enormous attention in automatic digital image processing and video processing in a different type of applications, which include wide variety and availability of cheap and powerful embedded computing and desktop systems. Also, it has been described as one of the best applications of image processing and analysis (Zou et al., 2007). Different statistical methods and algorithms such as Principal Component Analysis or Eigenface (PCA) (Zakariya et al., 2011), Local Binary Pattern (LBP) (Jiang & Guo, 2007) and Independent Component Analysis (ICA) (Jiang et al., 2008) algorithms have been developed for face recognition purposes.

Due to continuous research, a significant improvement in recognition performance is obtained over years (Borade & Adgaonkar, 2011). Characteristic faces are more easily recognized than typical faces. Low frequency bands contain information that determines the sex of the specific subjects, while recognition of individuals depends on the high frequency features. The global description is determined by the low frequency, while the finer descriptions high frequency modules give to the finer information required for the identification procedure (Yunyi et al., 2009; Shen et al., 2007;

Kasinski et al., 2008). The core task of this paper work is to investigate how the recognition performance can be enhanced and speeded up. Therefore, image transformation approach is used as a pre-processing stage before the feature extraction stage.

The rest of the paper is organized as follows; section 2 briefly describes SIFT algorithm, wavelet transform and proposed approach, section 3 shows the results using PUT face database and pertaining discussions, finally section 4 includes the conclusion.

2. Feature Extraction Method

2.1 Scale-Invariant Feature Transform

Scale-Invariant Feature Transform (SIFT) was developed by D. Lowe (Eleyan et al., 2008). SIFT is able to detect and extract distinctive features from different face images in order to achieve robust and stable matching between different face images of the same subject (person) with various facial expressions, face poses, and the features extracted form face images are scale, illumination and rotation invariance.

Figure 1 shows four important stages involved for detecting keypoints in the SIFT algorithm.

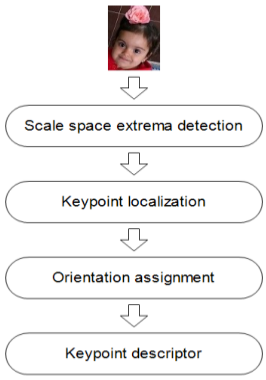

Figure 1: SIFT features extraction process.

In the initial stage a difference of Gaussian (DoG) (Lowe, 2004) was used to detect specific features and points which are orientations and scale invariance. In the stage of localizing key points, they are filtered with a predefined model which is based on their stability. A few orientations are given to the results using local image gradient. In the final stage, around each key point region; at different selected scales measurements applied on the image gradients. Figure 2 shows examples of key points extracted with SIFT features.

Figure 2: Interest points in face image.

2.2 Wavelet Transform

2D-DWT and GWT are mostly used as tunable filters suitable in detecting and extracting orientation information from the image. Apart from orientation, invariant to illumination property makes them appropriate to capture phase information of the pixels. Additionally, it is also an effective method to capture the texture of images. A Gabor wavelet filter is a Gaussian kernel function modulated by a sinusoidal plane wave as in Equation (1).

$$\psi_g(\mathrm{x},\mathrm{y}) = \frac{f2}{\eta\gamma\pi}\exp(\beta^2 y'^2 - \alpha^2 x'^2)\exp(2\pi\, j\, f\, x')$$
$$x' = x\cos\theta + y\sin\theta, \qquad (1)$$
$$y' = y\cos\theta - x\sin\theta,$$

where f is the dominant frequency of the sinusoidal plane wave, α is the sharpness of the Gaussian along the major axis parallel to the wave, θ is the anticlockwise rotation of the Gaussian and the envelope wave, and β is the sharpness of the Gaussian minor axis perpendicular to the wave. $\gamma = f/\alpha$ and $\eta = f/\beta$ are used to keep frequency and sharpness ratio in constant state. The 2D Gabor wavelet as defined in Equation (2) has Fourier transform:

$$\psi_g\,(u,v) = \exp\left(-\pi^2\left(\frac{(u'-f)^2}{\alpha^2} + \frac{v'^2}{\beta^2}\right)\right)$$
$$u' = u\,cos\theta + v\,sin\theta, \qquad (2)$$
$$v' = v\cos\theta - u\sin\theta.$$

Figure 3 shows the magnitude and phase of the Gabor wavelets for 1 scale and 8 angels, respectively. At all levels the wavelet is a Gaussian bandpass filter. Gabor wavelets have various features and properties that could be used in different ways and applications. One of the most distinctive and important features is directional selectivity. With this feature, one can orient Gabor wavelets in any desired direction.

Image features that are aligned in the same direction respond strongly while the features that are in other directions respond weakly. Space frequency analysis was used to detect local features precisely in any face image. One of the best methods that can be used between spatial resolution and frequency resolution is Gabor functions. the maximum amount of information can be extracted from local regions of an image by Gabor wavelets using their optimal frequency-space localization property (Eletan et al., 2008).

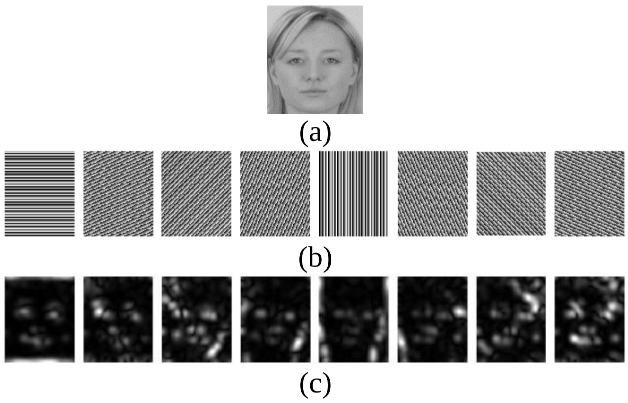

Figure 3: (a) The original image, (b) the magnitude and (c) the phase of the Gabor kernels at one scale and eight orientations

The 2D-DWT of a signal is performed by repeating the 2D analysis filter bank on the low pass sub image. Here, in the processing of each scale four sub images are used instead of one. 2D wavelet transform has relation with three wavelets. Repetition of the filtering and decimation process on low-pass outputs made multiple levels (scales).

In Figure 4 DWT transformation applied on face image, outputs four different sub images, namely; approximate, horizontal, vertical and diagonal.

Figure 4: 2D-DWT transform on face image

3. Proposed Approach

The proposed approach uses transformation of face images using DWT or GWT. SIFT is used to extract features from generated sub images. Figure 5 describes the block diagram of our proposed approach.

At first stage, face images transformed by applying DWT or GWT. Application of DWT or GWT will generate 4 sub images or 8 sub images, respectively. Gabor wavelets have various features and properties that could be used in different ways and applications. One of the most distinctive and important features is directional selectivity. While DWT has limited directional selectivity restricted to four namely; approximate, horizontal, vertical and diagonal. SIFT algorithm will be applied on these sub images to get the interest key-points. Salient features will be extracted from key-points. After comparison with sub images stored in the database, scores will be assigned to each subject for each sub image. At final stage, the scores obtained from each sub image will be fused as the final score and then decision will be made based on the highest recorded score.

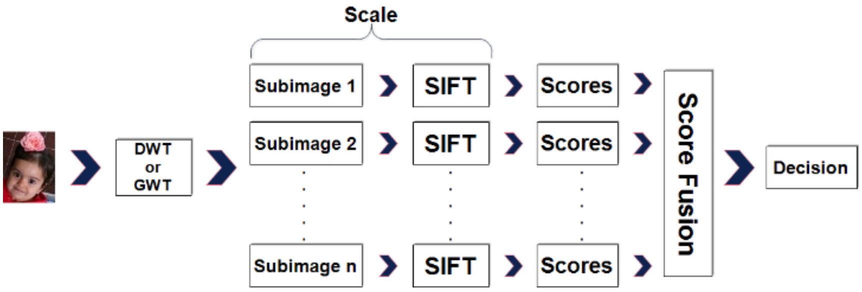

Figure 5: The block diagram of the proposed approach

4. Experimental Results

Experiments are performed to evaluate the performance of the proposed approach, and the results are compared with that of using SIFT. The dataset we used in the experiment is PUT dataset (Kasinski et al., 2008) were images have different head pose variations and are taken at different times. There are 100 subjects with 10 images per subject making a total of 1000 images. For most of the experiments in each dataset, 5 randomly chosen face images is considered as the gallery (train) set and the remaining face images are considered as the probe (test) set.

In all of the experiments, performances of SIFT, DWT-SIFT and GWT-SIFT approaches are compared using the average results of 10 runs of the program. At each run, different randomly gallery images were chosen for each subject. At first experiment, SIFT was applied with 50% of images are used in probe set while the rest are used as the gallery set. The results of using different number of subjects are shown in Table 1. Just like other biometric systems increasing the number of subjects will affect the performance of the system. With less number of subjects, we obtained high performance (98.4% for 10 subjects). Increasing the number of subjects degraded the performance of the system (93.9% for 100 subjects).

Table 1: Performance of SIFT using PUT face database

# of subjects	Recognition Rate %
10	98.40
30	96.73
40	96.60
60	94.40
80	94.28
90	94.38
100	93.90
Average	95.52

In second experiment, we applied 1 scale and 2 scales transformations on images, using different transformation filters (like Daubechies wavelets). Daubechies wavelets (db1, db2, db3, …) numbers refers to the number of vanishing moments. Basically, the higher the number of vanishing moments, the smoother the wavelet and longer the wavelet filter. For DWT-SIFT we can conclude that there is approximately ~4% difference between 1 scale and 2 scales transformation. The highest score goes to (db5) which was for 1-scale (88.92%) and 2-scales were (92.15%). Figure 6 shows differences between 1-scale and 2-scales transformation with different filters.

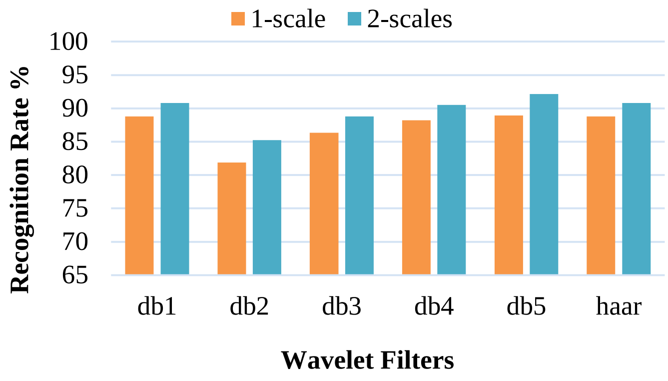

Figure 6: Performance of DWT-SIFT with 1-scale and 2-scales transformation

In third experiment, the performance of our proposed approach was completely different when we applied GWT on images before extracting features from it. 1 scale and 8 orientations were used. As the resulting 8 subimages from GWT were complex, the SIFT did not work properly on real or imaginary parts separately. To overcome this problem, we performed our approach using the magnitude ($GWT_{(Mag)}$-SIFT) or both magnitude and phase ($GWT_{(Mag+Phs)}$-SIFT) of each subimage. The performance of proposed approach is tabulated in Table 2.

Table 2: Recognition rate of GWT-SIFT using 1 scale and 8 orientations

# of Subjects	$GWT_{(Mag)}$-SIFT	$GWT_{(Mag+Phs)}$-SIFT
10	99.80	100.00
30	99.27	99.20
40	99.25	99.15
60	99.27	99.16
80	99.39	99.36
90	99.22	99.25
100	99.07	99.09
Average	99.32	99.32

The performance of proposed approach using phase of transformed images is ~4% higher than conventional SIFT algorithm. The rate of recognition performance of proposed approach decreasing slowly compared to SIFT. In forth experiment, different number of subjects in gallery set is used to test the performance of SIFT, DWT-SIFT and GWT-SIFT. As shown in Figure 7 the performance of GWT-SIFT was always higher compared to SIFT and DWT-SIFT.

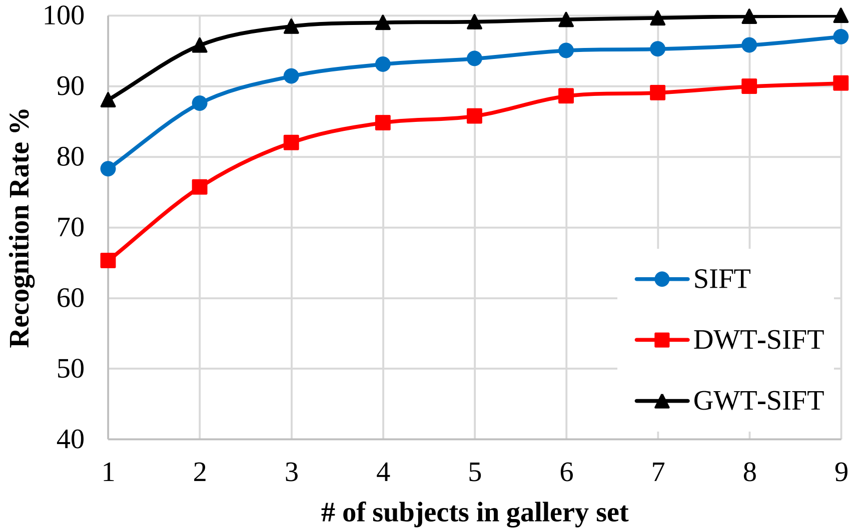

Figure 7: The performance of SIFT, DWT-SIFT and GWT-SIFT with different size of subjects

5. Conclusion

In this paper, SIFT was used to extract features from face images. The approach is based on wavelet transforms which are proposed to improve the recognition performances of SIFT descriptor. The first approach is based on DWT namely; DWT-SIFT. The second approach is based on GWT namely; GWT-SIFT. The DWT or GWT is applied to the image as a preprocessing stage before conventional SIFT is applied. SIFT is applied on the obtained subband images separately. The recorded scores from each subband image is then fused together to get the final score and make more accurate decision. The results obtained show that the fusion of matching scores of SIFT descriptor on the multiresolution images substantially improved the recognition performance.

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