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Spectral Graph Wavelet Theory Based Person Authentication System Using Multispectral Palmprint Images

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Abstract

Person authentication plays an important role in security based day to day life activities such as access control, identity recognition, data management and forensics. In this paper, palmprint based person recognition system is proposed by exploiting Spectral Graph Wavelet Theory (SGWT). Palmprint is a kind of human physiological trait and it has significant potential and discriminative features for person recognition. To extract features, palmprint images undergo SGWT decomposition. Then all the sub bands are fused and energy is computed as feature vectors for classifier training using nearest neighbor. The performance of proposed system is investigated on PolyU multispectral palmprint database images. Experimental results show that the proposed system achieves over 98% on blue spectral palmprint images.

Key words: Palmprint recognition, spectral graph wavelet theory, nearest neighbor classifier, chebyshev polynomial

1. INTRODUCTION

During the last two decades, numerous automatic personal authentication systems using various physiological traits such as fingerprint, face, iris, teeth and palmprint are developed. Among the traits, palmprint possess several key characteristics; uniqueness to person, resistance to aging, universality and ease of measurability. In this section, various techniques in associated with palmprint based authentication system are explained. Heart line extraction based palmprint classification is presented in [1].At first, Region of Interest (ROI) that contains only heart lines is obtained using boundary tracing and rotation based approaches from palmprint images. In feature extraction, Sobel gradient thresholds are adapted to extract the heart line from the ROI. Finally palmprint images are classified based on the regions that the heart line traverses in the palmprint.

Principal line based palmprint image classification is demonstrated in [2]. Initially palmprint database is divided into two groups; right hand group and left hand group. After separation of palmprint, each group is classified based on the distance travelled by principal line. Finite Ridgelet Transform (FRIT) based multi-scale palmprint classification is implemented in [3]. At first, palmprint images are decomposed by FRIT at various scale and angle. It produces higher and lower frequency coefficients. As lower frequency coefficients possess linear feature, it is transformed into feature vector and Support Vector Machine (SVM) is adapted for palmprint classification.

Palmprint features based personal authentication system is designed in [4]. It is composed of two computational modules: enrolment and verification modules. Sobel and morphological operations are performed to obtain palm-print features. Finally, reference feature templates for a specific user are generated for later classification. The back propagation neural network is used for verification. Hierarchical decomposition based palmprint image classification is described for personal verification in [5]. The principal palmprint features are extracted from the decomposed palmprint coefficients followed by dominant point extraction from the images at different resolutions.

Wavelet transform based palmprint recognition is discussed in [6]. Wavelet transform is employed for energy feature extraction. Due to high dimensionality of wavelet energy features, Principal Component Analysis (PCA) is exploited as dimension reduction approach for palmprint classification. Modified digital curvelet transform based palmprint recognition is described in [7]. Discrete Meyer wavelet transform is adapted for palmprint image decomposition instead of "à trous" transform. After that each decomposed sub bands undergoes into Ridgelet transformation to obtain feature for palmprint recognition.

Eigen space technique based palmprint image recognition is demonstrated in [8]. Initially the training palmprint images are transformed into small eigenpalms also called small set of feature by means of Karhunen-Loeve transform. Then unknown palmprint image is recognized by projecting subspace spanned by the eigenpalms using Euclidean distance classifier. Two Dimensional PCA (2DPCA) based palmprint recognition is introduced in [9]. In order to reduce dimension in both row and column direction, 2DPCA is applied. Wavelet energy feature based palmprint identification is implemented in [10]. To extract energy feature, multiresolutional wavelet transform is exploited up to 5^{th} level of decomposition. The city block measure is adapted for palmprint recognition.

Texture features based palmprint authentication is described in [11]. A 2D Gabor filter is used to extract texture features and palmprint images are compared in terms of their hamming distance for authentication. Hierarchical approach based palmprint image identification is illustrated in [12]. The global texture energy with high convergence of inner palm similarities and dispersion of discrimination is used to guide the dynamic selection of a small set of similar candidates from the database at coarse level. Finally point based image matching is performed on the selected similar patterns.

Discrete curvelet transform based palmprint recognition is introduced in [13]. The dominant spectral features are extracted as feature vector by employing curvelet transform. Registration approach based palmprint identification is described in [14]. Fourier mellin transformation is used to measure the similarity between two palmprint images. Phase based image matching algorithm is implemented in [15] for palmprint recognition. Phase based image matching is performed by 2D discrete Fourier transform.

In this study, an efficient palmprint recognition system is presented based on SGWT approach. This paper is structured as follows. A brief explanation about SGWT is described in section 2. The proposed palmprint recognition system based on SGWT is given in section 3. The discussions about the results obtained by the proposed system are given in section 4 and conclusion is made is section 5.

2 SPECTRAL GRAPH WAVELET THEORY

The spectral graph wavelet transform [16] is generated by wavelet operators that are operator-valued functions of the Laplacian. A measurable function of abounded self-ad joint linear operator on a Hilbert space is defined using the continuous functional calculus [17]. This is achieved using the spectral representation of the operator. In particular, for our spectral graph wavelet kernel g, the wavelet operator $T_g = g(L)$ acts on a given function f by modulating each Fourier mode as

$$T_g \hat{f}(l) = g(\lambda_l)\hat{f}(l) \tag{1}$$

Employing the inverse Fourier transform yields

$$(T_g f)(n) = \sum_{l=0}^{N-1} g(\lambda_l)\hat{f}(l)\chi_l(n) \tag{2}$$

The wavelet operators at scale t are then defined by $T_g^t = g(tL)$. It should be emphasized that even though the "spatial domain" for the graph is discrete, the domain of the kernel g is continuous and thus the scaling may be defined for any positive real number t. The spectral graph wavelets are then realized through localizing these operators by applying them to the impulse on a single vertex, i.e.

$$\psi_{t,n} = T_g^t \delta_n \tag{3}$$

Expanding this explicitly in the graph domain shows

$$\psi_{t,n}(m) = \sum_{l=0}^{N-1} g(t\lambda_l)\chi_l^*(n)\chi_l(m) \qquad (4)$$

Formally, the wavelet coefficients of a given function f are produced by taking the inner product with these wavelets, as

$$W_f(t,n) = \langle \psi_{t,n}, f \rangle \qquad (5)$$

Using the orthonormality of the $\{\chi_l\}$, it can be seen that the wavelet coefficients can also be achieved directly from the wavelet operators, as

$$W_f(t,n) = (T_g^t f)(n) = \sum_{l=0}^{N-1} g(t\lambda_l)\hat{f}(l)\chi_l(n) \qquad (6)$$

By construction, the spectral graph wavelets $\psi_{t,n}$ are all orthogonal to the null eigenvector χ_0, and nearly orthogonal to χ_l for λ_l near zero. In order to stably represent the low frequency content of f defined on the vertices of the graph, it is convenient to introduce a second class of waveforms, analogous to the low pass residual scaling functions from classical wavelet analysis. These spectral graph scaling functions have an analogous construction to the spectral graph wavelets. They will be determined by a single real valued function $h: R^+ \to R$, which acts as a low pass filter, and satisfies $h(0) > 0$ and $h(x) \to 0$ as $x \to 0$. The scaling functions are then given by $\phi_n = T_h\delta_n = h(L)\delta_n$, and the coefficients by $S_f(n) = \langle \phi_n, f \rangle$.

3. PROPOSED METHOD

The goal of this proposed system is to recognize a person to authenticate and to prevent forged access by means of physiological palmprint trait. The proposed palmprint recognition system is composed of two general computational modules: feature extraction and recognition. On account of person recognition SGWT energy features and nearest neighbor classifier is used. The schematic model of the proposed feature extraction module for palmprint recognition is shown in Figure 1.

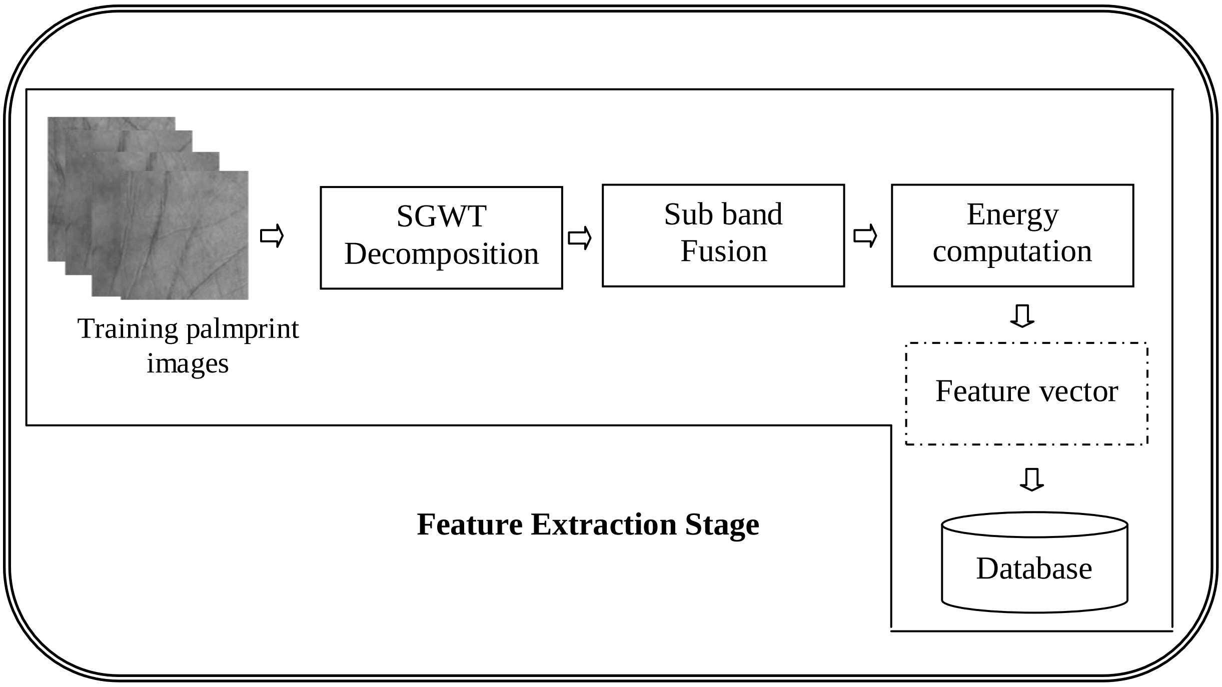


Fig.1 Feature extraction stage of the proposed palmprint recognition system

3.1 Feature Extraction

The process of extracting dominant features is the first step in most of the machine learning and computer vision algorithms. It reduces the amount of redundant data presented in a given image sample despite the fact that retaining discriminative image information. On account of feature extraction, SGWT is adapted at various level of decomposition that provides synchronized localization in both time and frequency domain. Thus, the given palmprint image undergoes SGWT decomposition for feature extraction. As SGWT is computed from the weighted graph with real valued vertices, it yields a high-dimensional feature vector. It may complicate the system performance. To ease the recognition system, the obtained sub bands are fused together and their response energies are computed as feature vector by squaring the fused coefficients. The extracted features from the training samples are stored for further classification process.

3.2 RECOGNITION STAGE

The second computational module of the proposed system is recognition stage. The schematic of the proposed recognition stage is shown in Figure 2.

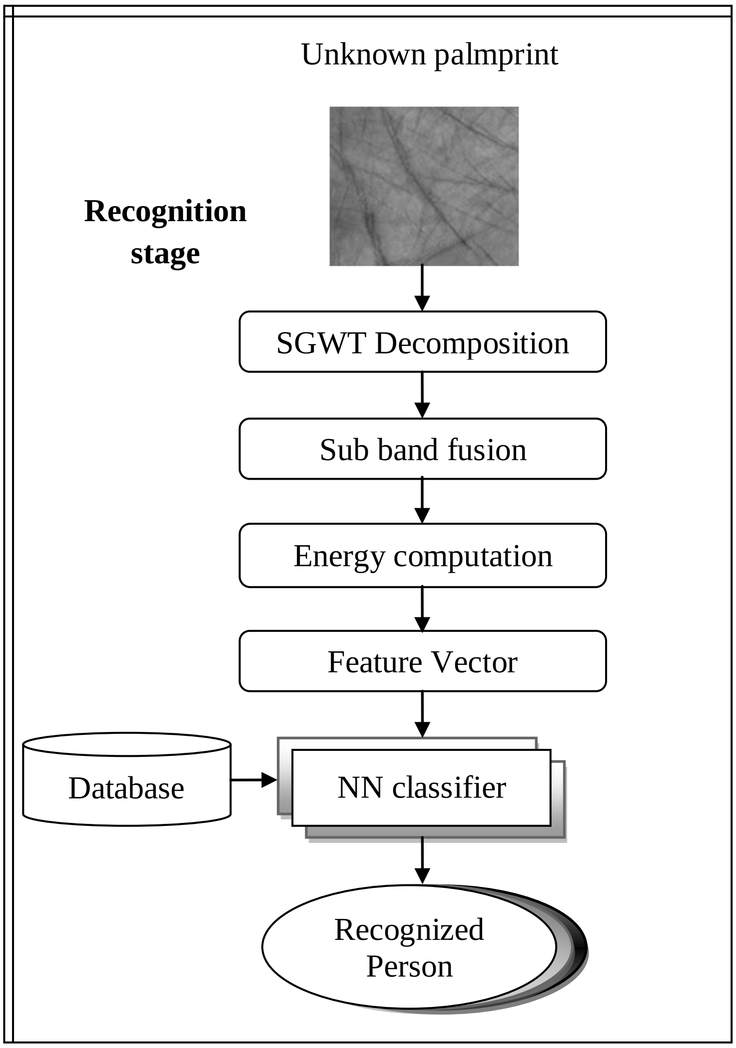
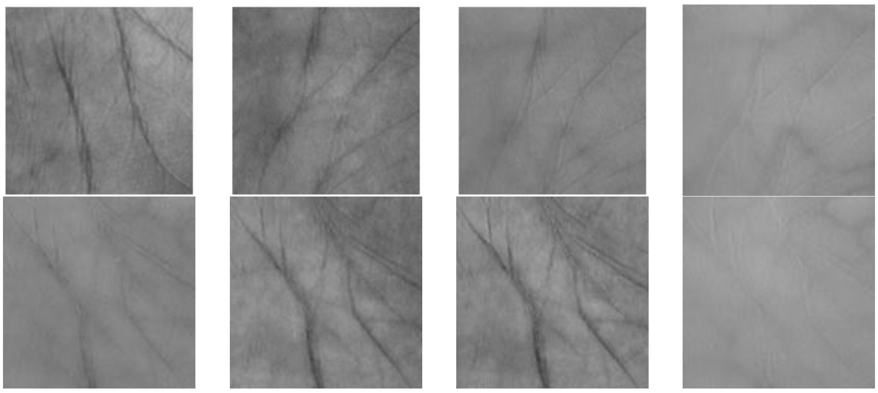


Fig. 2 Recognition stage of the proposed palmprint recognition system

At first, the proposed feature vector is extracted for the test palmprint image in this stage. The feature vector of test sample is analyzed with the feature vectors in the database by nearest neighbor classifier using euclidean distance. It provides Euclidean distances as many as training samples. Then, the authentication is done by the class label which has the minimum distance between the test sample and a particular training sample.

4. RESULTS AND DISCUSSION

In this section, the evaluation of the proposed palmprint recognition system based on SGWT is discussed. This study uses ROI images of Hong Kong Polytechnic University (PolyU) multispectral palmprint database [18] for performance analysis. ROI images are extracted using the algorithm in [19]. The palmprint images in this database are collected from 250 volunteers including 195 males and 55 females. The age group of volunteers is 20 to 60 years and 4 kinds of sensors; red, green, blue and Near Infra Red (NIR) are used. The palmprint images are captured in two successive sessions with average periods of 9 days. Figure 3 shows the sample palmprint images from the multispectral palmprint database.



(a) (b) (c) (d)

Fig. 3 Sample palmprint images (a) Red illuminated image (b) Green spectral image (c) Blue illuminated image (d) NIR

The performance of the proposed palmprint recognition system is validated in terms of classification accuracy. It is termed as the ratio of correctly classified images into total number of tested palmprint images. Table 1 to 4 shows the classification accuracy of the proposed palmprint classification system respective with red, green, blue and NIR palmprint images. As the proposed palmprint recognition system is treated as a classification system, the palmprint images captured in the first session are used for training and the second session images are used for testing the proposed approach. For evaluation, five disjoint set of images, each having 40 users are selected and the classification accuracy of each disjoint set is computed. The accuracies shown in the tables are the average recognition accuracy computed from the accuracies of five disjoint set of images. While calculating SGWT decomposed image, the chebyshev polynomial of Laplacian applied to the input vector is 10.

Table 1 Recognition accuracy of the red illumination images using SGWT

# Decomposition Level	# training samples					
	1	2	3	4	5	6
1	78.09	87.45	91.28	92.56	93.00	93.08
2	74.82	84.75	88.44	90.44	91.36	91.33
3	74.05	84.50	88.39	90.38	91.21	91.17
4	73.14	83.80	87.89	90.00	90.57	90.67
5	73.14	83.80	87.72	90.00	90.57	90.67

Table 2 Recognition accuracy of the green illumination images using SGWT

# Decomposition Level	# training samples					
	1	2	3	4	5	6
1	45.05	58.10	64.22	66.25	65.57	62.67
2	41.18	54.60	60.89	62.75	61.71	57.92
3	40.86	54.50	60.67	62.44	61.29	57.58
4	39.91	53.20	59.83	61.69	60.50	56.67
5	39.73	53.20	59.72	61.63	60.14	56.08

Table 3 Recognition accuracy of the blue illumination images using SGWT

# Decomposition Level	# training samples					
	1	2	3	4	5	6
1	88.91	94.60	96.28	97.00	96.93	88.91
2	86.68	92.80	94.00	95.56	95.71	86.68
3	86.41	92.40	93.89	95.31	95.43	86.41
4	85.59	91.90	93.11	94.81	94.71	85.59
5	84.86	91.55	92.67	94.25	94.07	84.86

Table 4 Recognition accuracy of the NIR illumination images using SGWT

# Decomposition Level	# training samples					
	1	2	3	4	5	6
1	90.14	94.15	95.56	95.25	94.93	94.58
2	88.00	92.10	93.44	93.56	93.07	92.67
3	87.77	91.90	93.33	93.19	92.86	92.58
4	87.05	91.35	92.61	92.63	92.36	92.00
5	87.41	91.30	92.83	92.88	92.43	91.83

It is observed from the tables 1 to 4 that the maximum classification accuracy achieved by the proposed system using red, green and blue illumination images are 93.08%,66.25%, 97% and 95.56% at 1-level decomposition respectively. At higher decomposition level, the performance of the system is gradually decreased due to redundant data. Among the four types of spectral images, the performance of the proposed system on green illuminated images produces very poor performance than others. As the decomposition of SGWT depends on the chebyshev polynomial, the impact on changing the polynomial order is also analyzed. Figure 4 to 7 show the performances of the proposed approach over different polynomial order used on different spectral palmprint images.

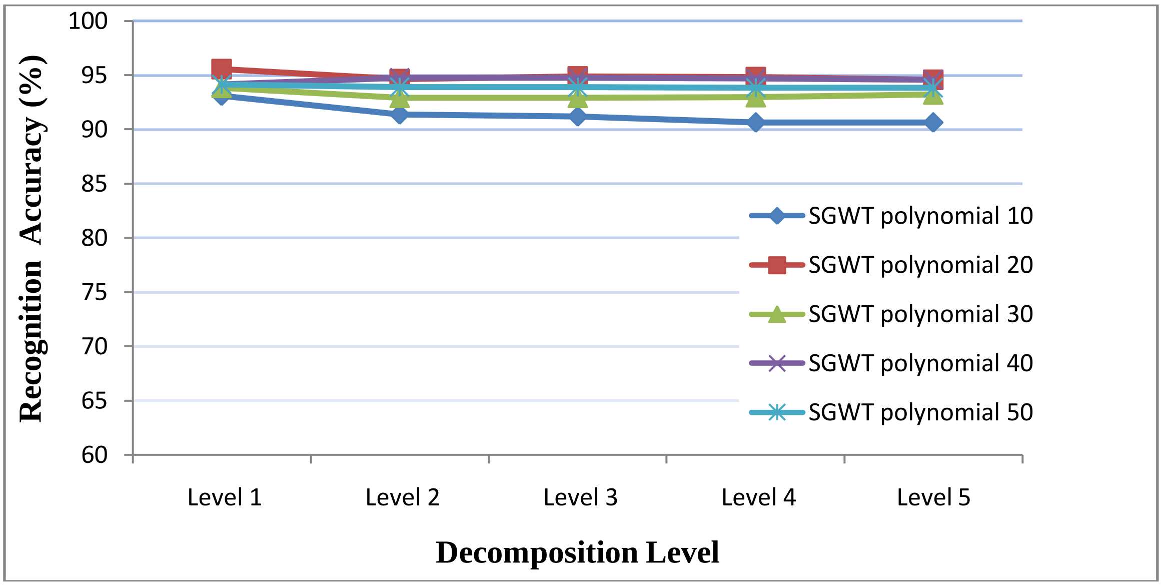


Fig. 4 Recognition accuracy vs. Polynomial order used in SGWT on the red spectral image

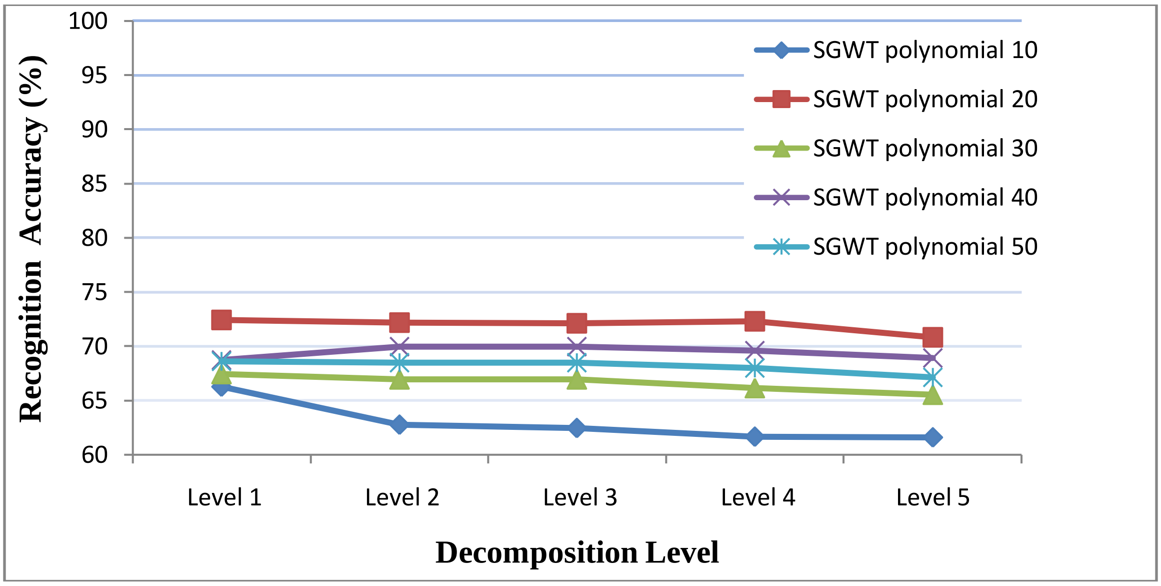


Fig. 5 Recognition accuracy vs. Polynomial order used in SGWT on the green spectral image

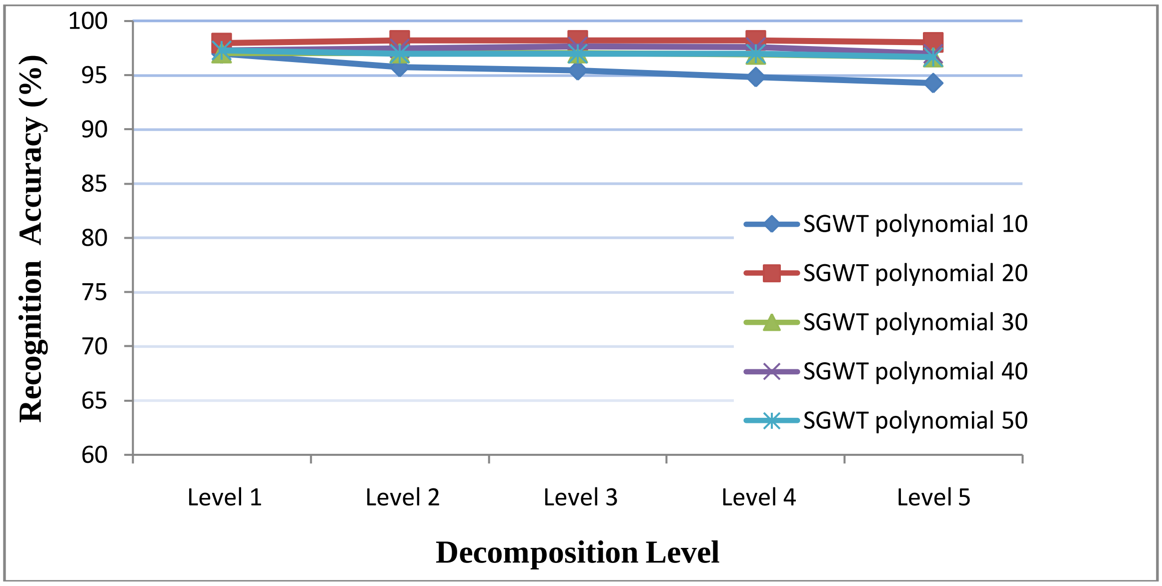


Fig. 6 Recognition accuracy vs. Polynomial order used in SGWT on the blue spectral image

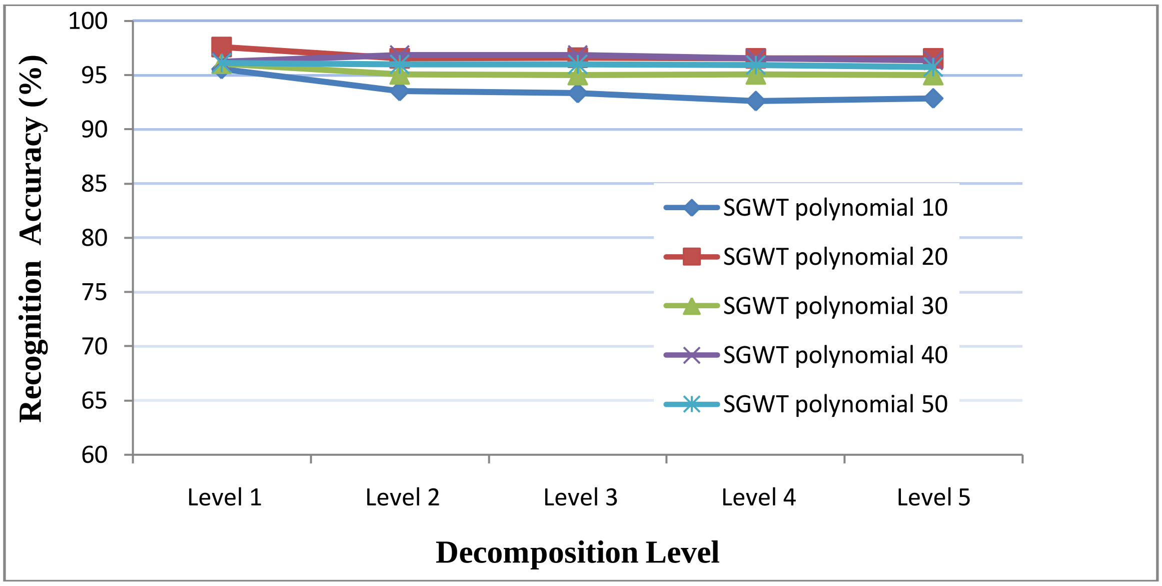


Fig. 7 Recognition accuracy vs. Polynomial order used in SGWT on the NIR spectral image

It is clearly observed from the figures 4 to 7 that the changes in the recognition accuracy on multispectral palmprint images are very low for any changes in the polynomial order up to 50 in multiples of 10. However, the maximum accuracy is achieved in the polynomial order of 20 and the blue sensor images produces higher accuracy of about 98.18%.

5 CONCLUSION

In this study, an efficient person authentication system is proposed based on SGWT using palmprint images. The discriminative palmprint features are extracted by performing SGWT decomposition at various decomposition levels and chebyshev polynomial orders. Due to the high dimensionality of SGWT coefficients, all sub-band coefficients are fused together and energy is computed as features. On account of person authentication, nearest neighbor classifier is adapted using Euclidean distance measure. The proposed palmprint classification system achieves satisfactory performance on PolyU multispectral palmprint database.

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