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Evaluating Feature Extractors and Dimension Reduction Methods for Near Infrared Face Recognition Systems

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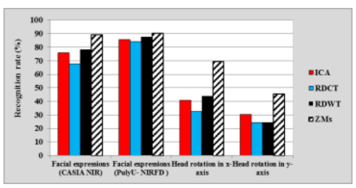
Graphical abstract



Abstract

This study evaluates the performance of global and local feature extractors as well as dimension reduction methods in NIR domain. Zernike moments (ZMs), Independent Component Analysis (ICA), Radon Transform + Discrete Cosine Transform (RDCT), Radon Transform + Discrete Wavelet Transform (RDWT) are employed as global feature extractors and Local Binary Pattern (LBP), Gabor Wavelets (GW), Discrete Wavelet Transform (DWT) and Undecimated Discrete Wavelet Transform (UDWT) are used as local feature extractors. For evaluation of dimension reduction methods Principal Component Analysis (PCA), Kernel Principal Component Analysis (KPDA), Linear Discriminant Analysis + Principal Component Analysis (Fisherface), Kernel Fisher Discriminant Analysis (KFD) and Spectral Regression Discriminant Analysis (SRDA) are used. Experiments conducted on CASIA NIR database and PolyU-NIRFD database indicate that ZMs as a global feature extractor, UDWT as a local feature extractor and SRDA as a dimension reduction method have superior overall performance compared to some other methods in the presence of facial expressions, eyeglasses, head rotation, image noise and misalignments.

Keywords: Face recognition; near infrared; comparative study; Zernike moments; undecimated discrete wavelet transform

Abstrak

Kajian ini menilai prestasi pengekstrak ciri global dan tempatan serta teknik-teknik pengurangan dimensi dalam domain NIR. Momen Zernike (ZMS), Analisis Komponen Bebas (ICA), Transformasi Radon + Transformasi Kosinus Diskret (RDCT), Transformasi Radon + Transformasi Wavelet Diskret (RDWT) digunakan sebagai pengekstrak ciri global manakala corak binari tempatan (LBP), Wavelet Gabor (GW), Transformasi Wavelet Diskret (DWT) dan Transformasi Wavelet Diskret Undecimated (UDWT) digunakan sebagai pengekstrak ciri tempatan. Untuk tujuan penilaian, teknik pengurangan dimensi seperti Analisis Komponen Utama (PCA), Kernel Analisis Komponen Utama (KPDA), Pembeza Analisis Linear + Analisis Komponen Utama (Fisherface), Pembeza Analisis Kernel Fisher (KFD) dan Pembeza Analisis Spektral Regresi (SRDA) digunakan. Eksperimen yang dijalankan ke atas pangkalan data CASIA NIR dan PolyU-NIRFD menunjukkan bahawa ZMS sebagai pengekstrak ciri global, UDWT sebagai pengekstrak ciri tempatan dan SRDA sebagai teknik pengurangan dimensi mempunyai prestasi keseluruhan yang amat tinggi berbanding dengan teknik-teknik yang lain terhadap pengecaman muka yang membabitkan ekspresi muka, cermin mata, putaran kepala, hingar imej dan ketidaksejajaran imej.

Kata kunci: Pengiktirafan muka; berhampiran inframerah; kajian perbandingan

■1.0 INTRODUCTION

Human face recognition is one of the most significant biometric approaches which is used to verify the identity of a living person based on his/her physiological characteristics by means of automatic methods. During the past decade face recognition (FR) has become the most active research area in the field of computer vision due to its potential value for many applications such as security systems, authentication, intelligent machines and surveillance as well as its wide challenges such as illumination variations, facial expression, head rotation, eyeglasses, noise and misalignments. Within the past two decades, numerous techniques have been proposed to solve aforementioned challenges and to propose accurate face recognition system. Most researchers have focused on visible face recognition due to undeniable fact that face recognition is one of the primary activities of the human visual system [1-4]. However the main problem with these approaches is the high dependency of system performance on external light, angle of light and even skin color [5-8].

Recently researchers have tended to use near infrared (NIR) imagery to solve illumination problem. Different methods are introduced in this domain. Some of them can be found in [9-12]. Generally, these methods can be classified into two main categories; (1) Global-based and (2) Local-based. In the global-based face representation, each dimension of the feature vector corresponds to some holistic characteristics of the face and hence encodes the global information embodied in every part of facial images. In contrast, in the local-based face representation, each dimension of feature vector contains the detailed information of face images that corresponds to a certain local region of the facial image. Some samples of global-based methods in NIR domain can be found in [10, 13] and some samples of local-based methods can be found in [14-16]. However most of related works in NIR domain focus on near infrared hardware design to solve illumination problem and as reported by Ghiass *et al*., none of the reported experiments examine the proposed method's performance in the context of all of challenges [17] .

As a result, in this paper, the performances of different commonly used global and local feature extractors as well as dimension reduction methods are evaluated in different cases. The global feature extractors are Zernike moments (ZMs) [10], Independent Component Analysis (ICA) [18], Radon Transform + Discrete Cosine Transform (RDCT) [4] and Radon Transform + Discrete Wavelet Transform (RDWT) [3] and the local feature extractors are Local Binary Pattern (LBP) [19], Gabor Wavelets (GW) [20], Discrete Wavelet Transform [21] (DWT) and Undecimated Discrete Wavelet Transform (UDWT) [22]. The dimension reduction methods are: Principal Component Analysis (PCA) [23], Kernel Principal Component Analysis (KPCA) [24], Linear Discriminant Analysis + Principal Component Analysis (Fisherface) [24], Kernel Fisher Discriminant Analysis (KFD) [25] and Spectral Regression Discriminant Analysis (SRDA) [26].

Our first goal is providing a better understanding of how performances of global and local methods varies with different types of challenges. Our second goal is to introduce the effective global and local feature extractor as well as dimension reduction methods which can lead to accurate face recognition system. To the best of our knowledge, algorithm developers in NIR domain have yet to explore this area of interest.

The remainder of this paper is organized as follows: In Section 2 brief reviews of global and local fature extractions as well as dimension reduction methods are discussed. Experimental results and performance analysis are given in Section 3. Conclusion and future work are drawn in Section 4.

■2.0 METHODS

Three procedures are discussed in this part. In the first part the global feature extraction method is proposed. This is followed by proposing a local feature extraction method to examine the performance of local based methods. Finally dimension reduction method is investigated.

2.1 Global Featute Extraction Method

The block diagram of global feature extraction method is shown in Figure 1(a). As shown in this figure firstly a normalized image in sent to the system. Then global feature extractor is applied on the whole images and the feature vector (FV) is resulted. For classification nearest neighbor classifier with Euclidian distance is employed and the results are considered.

2.2 Local Feature Extraction Method

The block diagram of the face recognition to generate local features is shown in Figure 1(b). As can be seen in this Figure in the first part of local feature extraction method, a normalized image is partitioned into 12 patches to produce stable and meaningful information. In the second step local feature extractor is applied on each patch and 12 feature vectors (FV) are generated. For classification decision fusion method is employed. In this step, face classification is run separately for each feature vector. The whole procedure of decision fusion is shown in Figure 2(a). It has two main steps as follows:

1. In the first part a confidence score is calculated for each class based on the distance values between the test face feature vector and feature vectors of the individuals in the database. This score represents the confidence of a classification into a class. The higher the score, the higher the confidence. Suppose c classes with m_i samples per class (m_i is the number of samples in ith class) are in the feature database, then the confidence score $S_{v,i}$ of the system decision for ith class and vth feature vector is defined as follows:

$$S_{v,i} = \frac{1}{\min\limits_{1 \le p \le m_i} d(FV_v(test), FV_{v,i,p}(database))} \qquad (1)$$

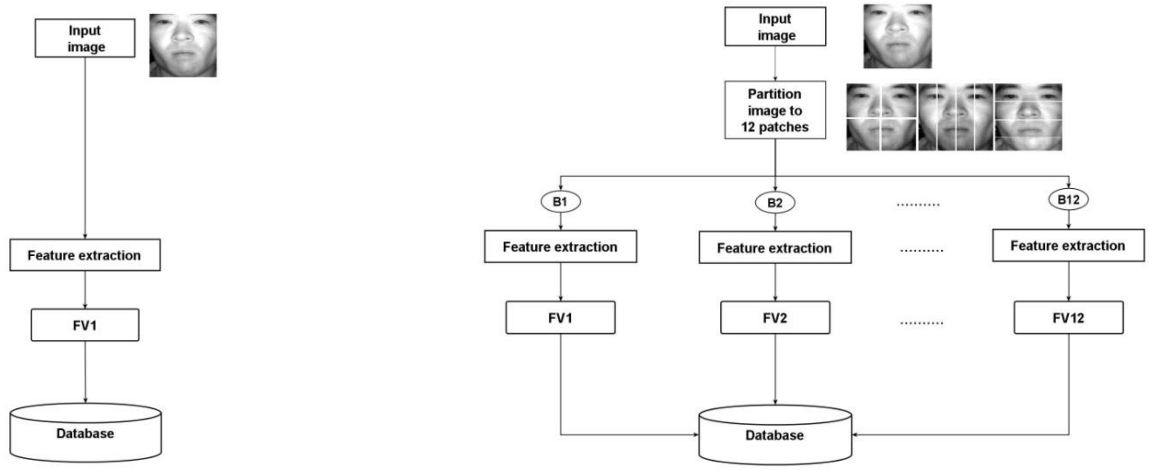
$$v = 1:12,\ i = 1:c$$

   where FV_v *(test)* is the vth feature vector related to test images, $FV_{v,i,p}$ (database) is the vth feature vector of pth sample in ith class related to database and d (.) stands for the distance function between two feature vectors.

2. As soon as confidence scores are calculated, the final decision is made through these confidence values by using sum rule [27].

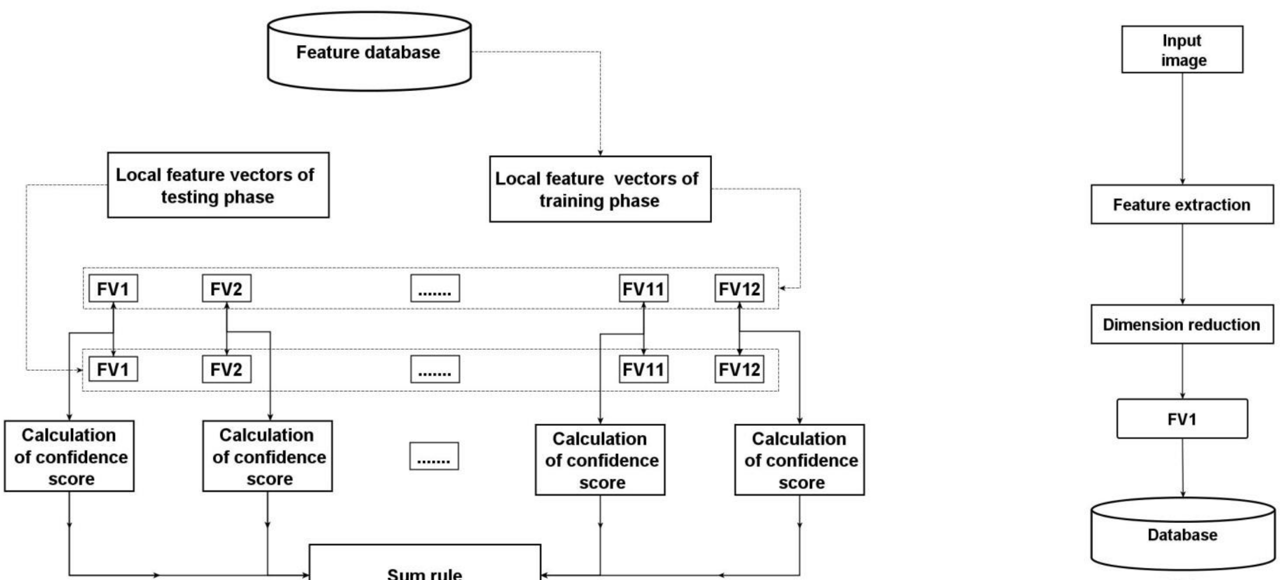
2.3 Dimension Reduction Method

The dimension reduction method for both global part and local part is the same as global and local featute extraction method. The main difference is employing a dimension reduction method after the feature extraction procedure. The block diagram of applying dimension reduction method in global feature extraction method can be seen in Figure 2(b).



(a) (b)

Figure 1 **(a)** The block diagram of global feature extraction (Training stage) (b) The block diagram of local feature extraction (Training stage)



(b)

Figure 2 **(a)** The block diagram of the decision fusion phase (b) The block diagram of global feature extraction method with dimension reductionmethod

■3.0 EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

In this section, we investigate the performance of the global feature extraction, local feature extraction and dimension reduction method using CASIA NIR database [18] and PolyU-NIRFD database* [44]. A comparative study is carried by using some popular global and local methods as well as dimension reduction methods. The global methods are as follows:

- Zernike moments (ZMs) [10]
- Independent Component Analysis (ICA) [18]
- Radon Transform + Discrete Cosine Transform (RDCT) [4]
- Radon Transform + Discrete Wavelet Transform (RDWT) [3]

The local methods are as follows:

- Local Binary Pattern (LBP) [19]
- Gabor Wavelets (GW) [20]
- Discrete Wavelet Transform (DWT) [21]
- Undecimated Discrete Wavelet Transform (UDWT) [22]

The dimension reduction methods which are used for the experiments (Figure 2(b)) are as follows:

- Principal Component Analysis (PCA) [23]
- Kernel Principal Component Analysis (KPCA) [24]
- Linear Discriminant Analysis + Principal Component Analysis (Fisherface) [24]
- Kernel Fisher Discriminant Analysis (KFD) [25]
- Spectral Regression Discriminant Analysis (SRDA) [26]

In the first part of this section, we briefly describe the database and preprocessing. This is followed by the experiments carried out to evaluate the performance of different methods and comparison between them. The following sets of experiments are carried out:

- Evaluating the performance of different global feature extractors in the presence of different challenges for generating global features.

* http://www4.comp.polyu.edu.hk/~biometrics/polyudb_face.htm

- Evaluating the performance of different local feature extractors in the presence of different challenges for generating local features.
- Testing the performance of different dimension reduction methods in the presence of different challenges.

3.1 Database and Image Preprocessing

The face images of CASIA NIR database and PolyU-NIRFD database (Figure 3(a)) is used in this work. The database specifications are described in Table 1. The CASIA NIR database includes images with facial expressions, eyeglasses, head rotation and images without any challenges. The PolyU-NIRFD database includes normal images, images with facial expressions and sharp head rotation, images with time-lapse and scale variations. However time-lapse and scale variations are out of scope of this paper. Hence the images with time-lapse and scale variations are not used in our experiments. The sizes of gallery set and probe set for both CASIA NIR and PolyU-NIRFD database are 500 and 1000 respectively. There is no overlap between gallery set and probe set. The flow of preprocessing is as follows.

1. Face images are aligned by placing the two eyes at fixed position (Figure 3(b)).
2. Face images are cropped to remove hair and background (Figure 3(c)).
3. Face images are resized to 64×64 with 256 gray levels to decrease computation time (Figure 3(d)). This resizing is decided experimentally as choosing a larger size does not significantly increase accuracy but increases computation time. The resized images still retain useful information for face recognition.

3.2 Evaluating the Performance of Different Global Feature Extractors in the Presence of Different Challenges for Generating Global Features

In this section seven experiments are conducted to determine the performance of different global feature extractors. To provide global features, the feature extractors are applied on the whole face. The specifications of feature extractors and the specification of gallery images and probe images are tabulated in Table 2 and 3 respectively. 3000 face images of 200 subjects (15 images per person) from CASIA NIR database and PolyU-NIRFD database including normal images, images with facial expressions, images with head rotation and images with eyeglasses are and used in our experiments. Some samples of used images from CASIA NIR database and PolyU-NIRFD are shown in Figure 4 and Figure 5 respectively. Table 4, Table 5, Figure 6 and Figure 7 show the results obtained from the analysis of different global methods in the presence of different challenges.
Based on results the following observations can be made:

1. As shown in Table 4 and Table 5, in the presence of head rotation and misalignment, ZMs have the best performance among other feature extraction methods. This result can be explained by the fact that ZMs generate global features which maintain the global structure of input images. Hence their performance is not highly affected when these challenges occurred in the face images. Further analysis shows that the performance of ZMs is not affected in the presence of facial expressions which highlights the good performance of ZMs to facial expression. The results here is consistent with the results reported in [28].
2. Strong evidence of ZMs deficiency to eyeglasses was found in this experiment. This result can be explained by the fact that ZMs generate global features, hence local changes such as eyeglasses affects the values of all moments. Hence its performance decreases highly in this case.
3. Since RDCT is based on low frequencies which are boosted by Radon transform and contributes to global features, its accuracy is highly affected when local variations such as facial expression and eyeglasses occur. Hence the performance of RDCT is the lowest in the presence of facial expressions and eyeglasses.
4. In the presence of noise, RDCT has the highest accuracy whereas ICA has the lowest accuracy. Because Radon transform is the line integral, it acts as a low - pass filter. So low frequencies of an input image are amplified. This makes the system more robust in the presence of noise in comparison with other methods. The results obtained boost the results presented in [4]. The deficiency of ICA to noise proves the high sensitivity of appearance-based methods to noise which has already been shown in [10].
5. Although the performance of ZMs is not as good as RDCT in the presence of noise, but it is still comparable with other methods.
6. As shown in Table 4 and Figure 5 the accuracy of RDWT is highly affected in the presence of misalignments and its accuracy is the lowest among other methods. This low performance is due to shift sensitivity of DWT. These findings further support the idea of the sensitivity of DWT to translation which was already highlighted in [29].
7 What is interesting in results is that, head rotation affects the recognition accuracy of methods considerably. A possible explanation for this is that that head rotations in *x*-axis and *y*-axis change in the visual appearances of the face image significantly and affect the performance of methods. Further analysis shows that the performances of the methods based on PolyU-NIRFD database decrease more highly than those of the methods based on CASIA NIR database. This is due to existence of images in PolyU-NIRFD with head rotation in *y*-axis which have sharper yaw and roll angles. Hence the appearances of images are changed more significantly which affect the results as well.

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

CASIA NIR database **PolyU-NIRFD database**

Figure 3 Proposed preprocessing method, (a) raw image, (b-c) preprocessing steps (d) the normalized images

Table 1 Summary of the CASIA NIR and PolyU-NIRFD database

	Database	
	CASIA NIR	**PolyU-NIRFD**
Acquisition device	Home-brew camera with 850 nm wavelength	JAI camera with 850 nm wavelength
No. of subjects	197	335
Number of still images per subject	20	100
Distance	50 centimeters and 100 centimeters	80 centimeters and 120 centimeters
Resolution	640×480	768×576
Format	BMP	JPG

Table 2 Settings for different global feature extractors used in performance evaluation

Methods	Specification
ZMs	ZMs up to order 10 are calculated for an image to generate global features. Since ZMs are complex valued, imaginary part, real part and magnitude of ZMs are used as data vector and they are concatenated together and a data vector is generated.
ICA	The number of independent components to be estimated equals to dimension of data. We use Gaussian function with parameter a=1 due to the best performance obtained by this value.
RDCT	It is a combination of Radon transform and discrete cosine Transform. The number of projections in Radon transform is 60 for angles 0-179 degrees due to the best performance of system by these values.
RDWT	It is a combination of Radon transform and discrete wavelet transform. The number of projections in Radon transform is 60 for angles 0-179 degrees. The decomposition level of DWT is 3 and the wavelet basis is "DB3'. The selected subband is "LLL3".

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

Figure 4 (a) Sample of normalized image used as gallery image (b-d) Sample of images with facial expressions, eyeglasses and head rotation in x-axis (CASIA NIR database)

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

Figure 5 (a) Sample of normalized image used as gallery image (b-d) Sample of images with facial expressions, left and right head rotation in y-axis (PulyU-NIR database)

Table 3 Specifications of training and testing images used in the different experiments

Challenge	Gallery image	Probe image	Database
Facial expression	3 normal images	3 images with facial expression	CASIA NIR database and PulyU-NIRFD database
Eyeglasses	3 normal images	3 images with eyeglasses	CASIA NIR database
Head rotation in *x*-axis	3 normal images	3 images with head rotation in *x*-axis	CASIA NIR database
Head rotation in *y*-axis	3 normal images	3 images with head rotation in *y*-axis	PulyU-NIRFD database
Noise	3 normal images	3 noisy images with SNR 22 dB	PulyU-NIRFD database
Misalignment	3 normal images	3 images with random translation, scale and rotation are used. The degree of translation, rotation and scale is [-2, 2], [-3^0, 3^0] and [0.95, 1.05] respectively	PulyU-NIRFD database

Table 4 Performance comparison of various global methods on CASIA NIR database and PulyU-NIR database (Mean±Std- Dev percent)

Methods	Facial expressions (CASIA NIR database)	Facial expressions (PulyU-NIR database)	Head rotation in *x*-axis (CASIA NIR database)	Head rotation in *y*-axis (PulyU-NIR database)
ICA	75.83 ± 3.58	85.73 ± 1.11	40.83 ± 4.24	30.23 ± 2.79
RDCT	67.70 ± 4.74	84.08 ± 2.36	32.62 ± 1.58	24.37 ± 0.75
RDWT	78.16 ± 5.21	87.50 ± 3.24	44.12 ± 2.95	24.50 ± 2.28
ZMs	**89.23 ± 1.21**	**90.43 ± 1.73**	**69.23 ±2 .34**	**45.32 ± 3.52**

Table 5 Performance comparison of various global methods on CASIA NIR database and PulyU-NIR database (Mean ± Std-Dev percent)

Methods	Eyeglasses	Noise	Misalignment
ICA	**83.66 ± 2.49**	66.28 ± 3.28	70.24 ± 2.40
RDCT	60.62 ± 3.33	**83.47 ± 2.20**	68.73 ± 2.43
RDWT	66.50 ± 2.77	81.92 ± 1.43	35.34 ± 4.29
ZMs	70.41 ± 1.42	81.58 ± 1.90	**84.71 ± 2.22**

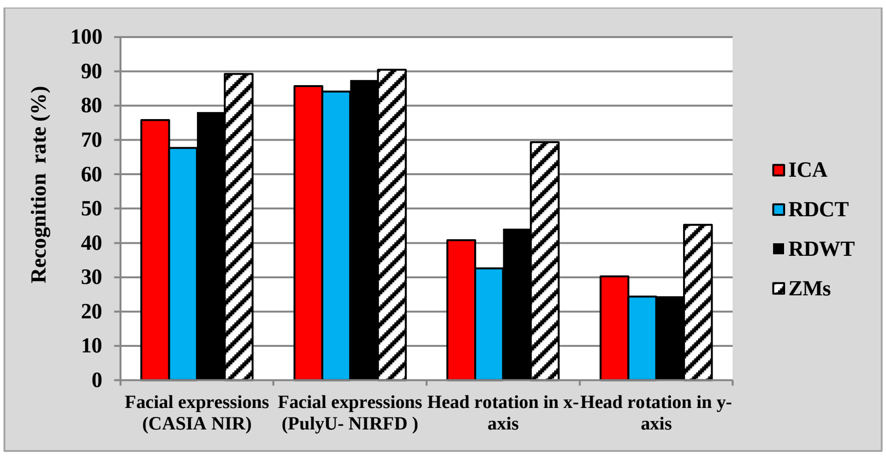


Figure 6 The performances of different global methods in the presence of facial expressions and head rotation

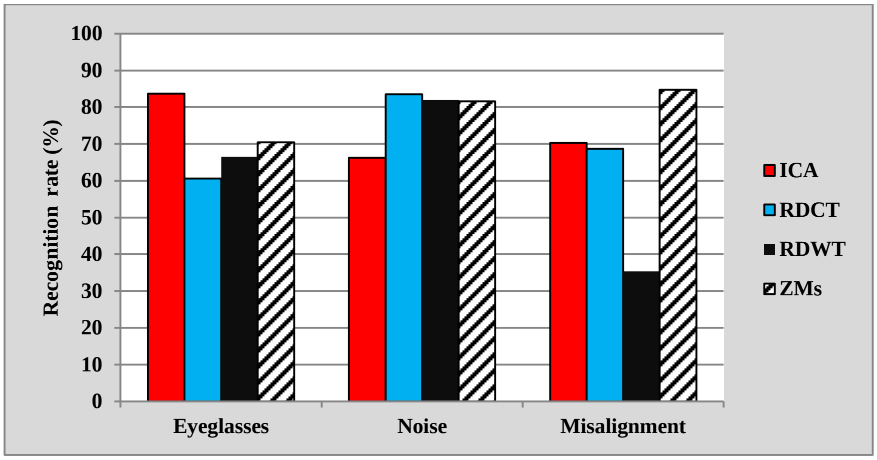


Figure 7 The performances of different global methods in the presence of eyeglasses, noise and misalignment

3.3 Evaluating the Performance of Different Local Feature Extractors in the Presence of Different Challenges for Generating Local Features

In this section the performance of different local feature extractors to generate local features are evaluated. The configurations of gallery set and probe image is the same as previous experiment. The specifications of local feature extractors are tabulated in Table 6. Table 7, Table 8, Figure 8 and Figure 9 show the results obtained from the analysis of different local methods in the presence of different challenges.

Based on results the following observations can be made:

1. As shown in the results UDWT has the best performance among other local feature extractors in the presence of different challenges.
2. By comparing the results of DWT and UDWT three conclusions can be made: First in the presence of facial expressions and head rotations UDWT performs better than DWT. The most likely cause is that UDWT generates full resolution subbands while in DWT they are decimated. So, when using UDWT, essentially more information is used even if the same subbands are employed. Second conclusion is that there is a significant difference between the recognition rate of DWT and UDWT in the presence of noise. This is because of decimation process in DWT which decreases the resolution of images of DWT and deteriorates the performance of systems subsequently. The third conclusion is that the deficiency of DWT to misalignments can be seen in this experiment. This finding corroborates the ideas of Li *et al.,* [29] who mentioned misalignments as one of the deficiency of DWT.
3. As can be seen in the results, GW has deficiency in the presence of facial expressions. This finding is in agreement with the findings reported in [3] which showed that facial expression deteriorates the performance of GW.
4. Most striking results to emerge is that when minor noise is added to the test images, the accuracy of LBP method drops sharply and it works even worse than GW and DWT in the presence of noise. The underlying reason is that LBP thresholds exactly at the value of the central pixel. Hence, original LBP tends to be sensitive to noise which limits its usability for video surveillance scenarios.

Table 6 Settings for different local feature extractors used in performance evaluation

Method	Specification
LBP	LBP histogram in (8,1) neighborhood using uniform patterns (LBP $^{U2}_{8,1}$) is used.
GW	Gabor Wavelets with five scales and eight orientations are used to derive the desirable facial features.
DWT	First an image is decomposed using DWT to level 3. Finally the coefficients of low and high frequencies in level 3 are used as features. The wavelet basis is "DB3'.
UDWT	All of the parameter settings are the same as DWT.

Table 7 Performance comparison of various local methods on CASIA NIR database and PulyU-NIR database (Mean±Std- Dev percent)

Methods	Facial expressions (CASIA NIR database)	Facial expressions (PulyU NIR database)	Head rotation in *x*-axis (CASIA NIR database)	Head rotation in *y*-axis (PulyU NIR database)
LBP	71.16 ± 3.35	82.91 ± 2.22	44.62 ± 3.61	36.62 ± 0.83
GW	57.87 ± 2.88	63.23 ± 1.87	67.11 ± 3.79	32.31 ± 2.49
DWT	83.32 ± 2.68	85.32 ± 1.08	70.23 ± 5.11	30.07 ± 3.91
UDWT	**89.22 ± 1.54**	**90.34 ± 2.71**	**74.39 ± 2.47**	**38.39 ± 2.98**

Table 8 Performance comparison of various local methods on CASIA NIR database and PulyU-NIR database (Mean±Std- Dev percent)

Methods	Eyeglasses	Noise	Misalignment
LBP	91.02 ± 3.72	5.23 ± 4.24	80.94 ± 1.08
GW	73.31 ± 1.65	65.45 ± 1.05	72.21 ± 3.37
DWT	86.43 ± 1.39	70.28 ± 4.04	63.22 ± 1.11
UDWT	**92.31 ± 0.85**	**90.23 ± 1.32**	**89.31 ± 2.72**

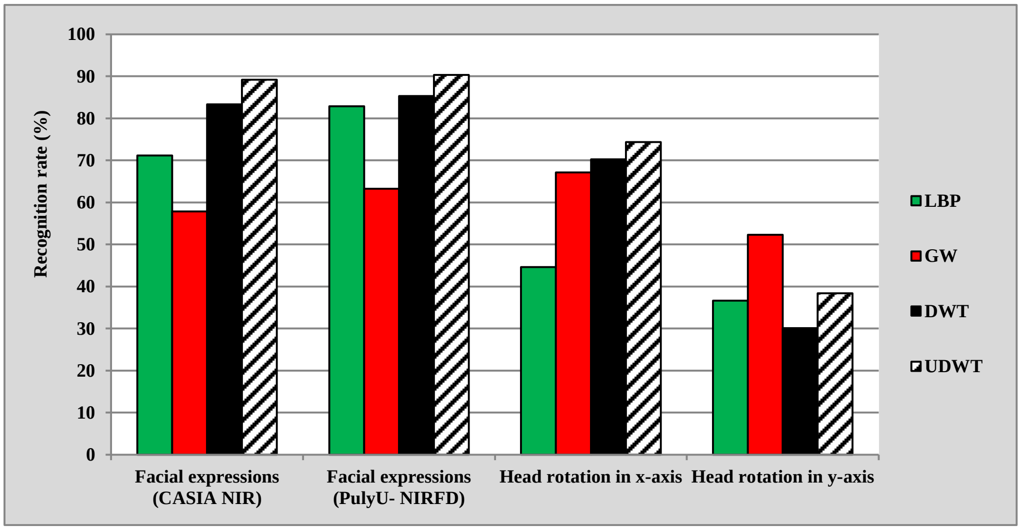


Figure 8 The performances of different local methods in the presence of facial expression and head rotation

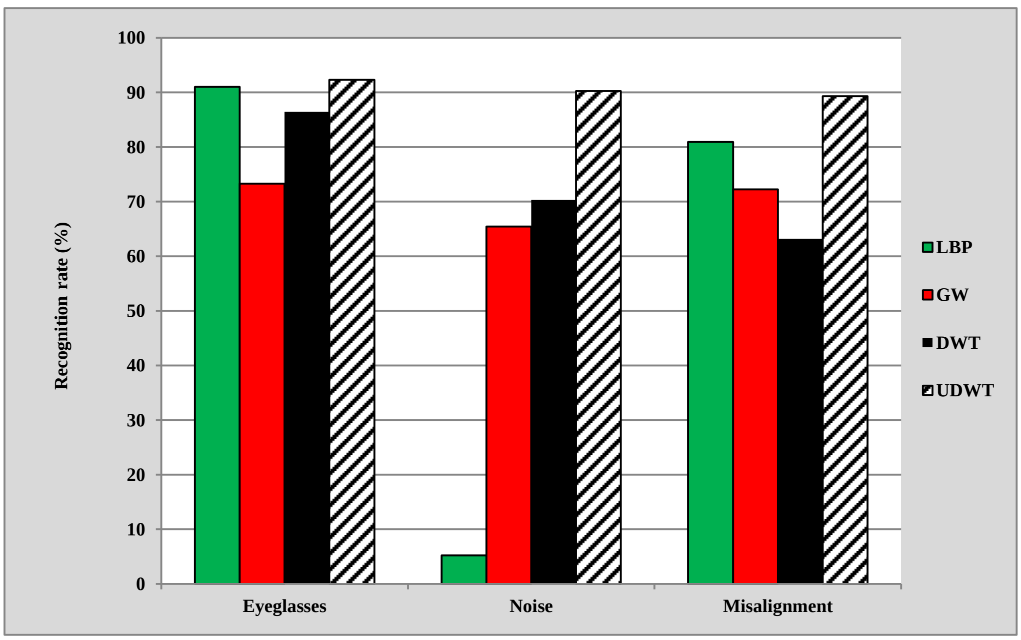


Figure 9 The performances of different local methods in the presence of eyeglasses, noise and misalignment

3.4 Testing the Performance of Different Dimension Reduction Methods in the Presence of Different Challenges

As can be seen from pervious sections ZMs and UDWT can be good choices as global and local feature extractor. Hence, in this section, the performance of these feature extractors are evaluated and enhanced by means of different dimension reduction methods. As a result, some experiments based on the 1000 facial images of 100 subjects (10 images per subject) belong to CASIA NIR database and PolyU-NIRFD database with different variations including smiling, nonsmiling, eyeglasses or no eyeglasses and head rotations are conducted. A random subset with 3 images per individuals is taken with labels to form the training set. The rest of the database is considered to be the testing set. The selected kernel of KPCA and KFD is polynomial and the degree of polynomial is set to 0.7 due to the best performance of system by these parameters. The configuration of ZMs and UDWT is the same as before. The average recognition rate with over 20 random splits is calculated for each method and the results are considered. Assuming the success rates are normally distributed, confidence intervals are also calculated. Confidence interval is one of the most useful criterion to evaluate the reliability of results. Smaller confidence intervals indicate the high preciseness of the method. Table 9, Table 10, Figure 10 and Figure 11 show the recognition rates, standard deviations and confidence intervals of ZMs and UDWT with different data reduction methods.

From the experimental results obtained for different dimension reduction methods, the following observations can be made:

1. According to the results, we can see that there is a significant improvement in the recognition rate when the dimension reduction methods are applied to ZMs and UDWT. The underlying reason is that high dimensional ZMs and UDWT features include both low and high discriminative features. When all of the features are used, classification is done based on the low-discriminable features, which is prone to errors. Hence, when a dimensionality reduction method is used, low-discriminable features are removed and the recognition rate is increased.
2. From Table 9 and 10, we observe that the maximum recognition rate with minimum standard deviation and the narrowest confidence interval is achieved by using SRDA. Further analysis based on Figure 9 and 10 shows that there is no overlap between the confidence interval of SRDA and other data reduction methods. It shows SRDA performs significantly better (in the statistical sense) than the other data reduction methods. Another important finding is that in all cases the superiority of regularized discriminant analysis methods such as SRDA to the classical ones such as Fisherface can be observed by comparing the recognition results and confidence intervals of ZMF, ZMSRDA, UDWTF and UDWTSRDA.
3. It is apparent from Figure 10 and Figure 11 that the confidence intervals of almost all of data reduction methods except SRDA overlap and there are no significant differences between the performances of data reduction methods. This finding corroborates the advantages of SRDA to other data reduction methods.

Table 9 Performance of ZMs with different data reduction methods

Method	Recognition rate along with standard deviation	Confidence interval
ZM	87.31 ± 3.11	[85.94, 88.67]
ZMPCA	90.23 ± 2.13	[89.29, 91.16]
ZMKPCA	91.49 ± 1.74	[90.72, 92.25]
ZMF	93.07 ± 1.21	[92.53, 93.60]
ZMKFD	93.54 ± 1.46	[92.90, 94.17]
ZMSRDA	**95.11 ± 1.03**	**[94.68, 95.59]**

Table 10 Performance of UDWT with different data reduction methods

Method	Recognition rate along with standard deviation	Confidence interval
UDWT	90.72 ± 2.94	[89.43, 92.00]
UDWTPCA	92.26 ± 2.09	[91.34, 93.17]
UDWTKPCA	91.33 ± 2.31	[90.31, 92.34]
UDWTF	95.12 ± 1.29	[94.55, 95.68]
UDWTKFD	94.01 ± 1.72	[93.25, 94.76]
UDWTSRDA	**96.48 ± 0.92**	**[96.07, 96.88]**

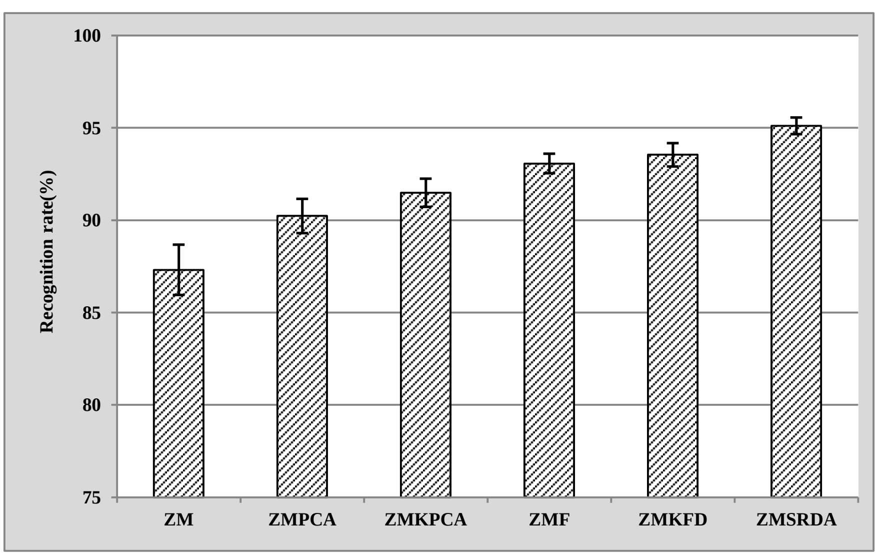


Figure 10 The performances of different dimension reduction methods combined with ZMs

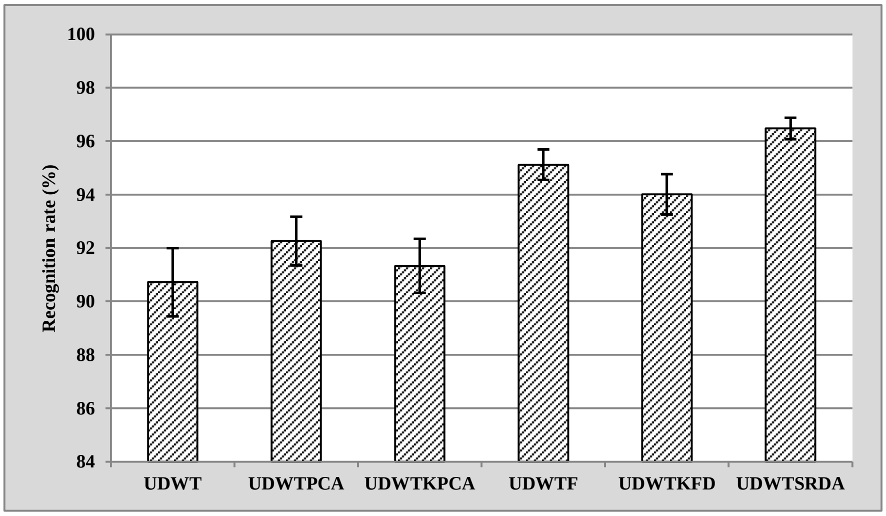


Figure 11 The performances of different dimension reduction methods combined with UDWT

4.0 CONCLUSION

The present study was designed to compare the performance of different global and local feature extractors as well as different dimension reduction methods in the presence of different challenges. The CASIA NIR database and PolyU-NIRFD database were used to compare the performance of different methods. In the first part of evaluation, the performances of different global feature extractors in the presence of the most common challenges were examined. This is followed by evaluation of various local feature extractors. Finally the evaluations of five dimension reduction methods were conducted. The following conclusions can be drawn from the present study:

- Both global and local features are necessary for proposing a accurate face recognition system.
- ZMs and UDWT are powerfull feature extractors which can be used as in NIR face recognition methods.
- SRDA has better performance than other data reduction methods and its usage can improve the performance of system considerably.

The study has gone some way towards enhancing our understanding the nature of different challenges and their relation to global and local features. Moreover, it makes several noteworthy contributions to deficiency of global and local feature extractor in the presence of the most common challenges in NIR domain. Our future work is to designing a feature extraction based on both global and local feature extractions in NIR domain for proposing accurate face recognition system.

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References

[1] Xu, Y., Q. Zhu, Z. Fan, D. Zhang, J. Mi, and Z. Lai. 2013. Using the idea of the sparse representation to perform coarse-to-fine face recognition. *Information Sciences*. 238(2013): 138–148.

[2] Jadhav, D.V. and R.S. Holambe. 2008. Radon and Discrete Cosine Transforms Based Feature Extraction and Dimensionality Reduction Approach for Face Recognition. *Signal Processing*. 88(10): 2604–2609.

[3] Jadhav, D.V. and R.S. Holambe. 2009. Feature Extraction Using Radon and Wavelet Transforms with Application to Face Recognition. *Neurocomputing*. 72(7): 1951–1959.

[4] Jadhav, D. V. and R. S. Holambe. 2010. Rotation, Illumination Invariant Polynomial Kernel Fisher Discriminant Analysis Using Radon and Discrete Cosine Transforms Based Features for Face Recognition. *Pattern Recog. Lett.* 31(9): 1002–1009.

[5] Moritz, S., A.H. Jorgen, and G.E. Erik. 2001. Physics-based Modelling of Human Skin Colour Under Mixed Illuminants. *Robotics and Autonomous Systems*. 35(3): 131–142.

[6] Adini, Y., Y. Moses, and S. Ullman. 1997. Face Recognition: The Problem of Compensating for Changes in Illumination Direction. *IEEE Trans. Pattern Anal. Mach. Intell.* 19(7): 721–732.

[7] Socolinsky, D. A., A. Selinger, and J. D. Neuheisel. 2003. Face Recognition with Visible and Thermal Infrared Imagery. *Comput. Vision Image Understanding*. 91(1): 72–114.

[8] Farokhi, S., S.M. Shamsuddin, J. Flusser, and U. Ullah Sheikh. 2012. Assessment of Time-Lapse in Visible and Thermal Face Recognition. *World Academy of Science, Engineering and Technology*. 62(2012-02-23): 540–545.

[9] Maeng, H., S. Liao, D. Kang, S.-W. Lee, and A. K. Jain. 2012. Nighttime Face Recognition at Long Distance:Cross-distance and Cross-spectral Matching. in *Asian Conference on Computer Vision*. Daejeon, Korea: ACCV.

[10] Farokhi, S., S.M. Shamsuddin, J. Flusser, U.U. Sheikh, M. Khansari, and J.-K. Kourosh. 2013. Rotation and Noise Invariant Near-infrared Face Recognition by Means of Zernike Moments and Spectral Regression Discriminant Analysis. *J. Electron. Imaging*. 22(1): 1–11.

[11] Farokhi, S., S.M. Shamsuddin, J. Flusser, U.U. Sheikh, M. Khansari, and J.-K. Kourosh. 2014. Near Infrared Face Recognition by Combining Zernike Moments and Undecimated Discrete Wavelet Transform. *Digit. Signal Process.* 31(2014): 13–27.

[12] Farokhi, S., S. Shamsuddin, U.U. Sheikh, and J. Flusser. 2014. Near Infrared Face Recognition: A Comparison of Moment-Based Approaches. in *The 8th International Conference on Robotic, Vision, Signal Processing & Power Applications*. Penang, Malaysia: Springer Singapore.

[13] He, Y., G.F. Feng, F. Liu, and H. He. 2010. Near Infrared Face Recognition Based on Wavelet Transform and 2DPCA. In *International*

Conference on Intelligent Computing and Integrated Systems. Guilin, China: IEEE.

[14] Li, S.Z., R. Chu, S. Liao, and L. Zhang. 2007. Illumination Invariant Face Recognition Using Near-Infrared Images. *IEEE Trans. Pattern Anal. Mach. Intell.* 29(4): 627–639.

[15] Zhang, B., L. Zhang, D. Zhang, and L. Shen. 2010. Directional Binary Code with Application to PolyU Near-Infrared Face Database. *Pattern Recog. Lett.* 31(14): 2337–2344.

[16] Zheng, Y. 2012. Near Infrared Face Recognition Using Orientation-based Face Patterns. In *International Conference of the Biometrics Special Interest Group (BIOSIG)*. Fraunhofer IGD, Darmstadt, Germany: IEEE.

[17] Shoja Ghiass, R., O. Arandjelović, A. Bendada, and X. Maldague. 2014. Infrared Face Recognition: A Comprehensive Review of Methodologies and Databases. *Pattern Recognition*. 47(9).

[18] Delac, K., M. Grgic, and P. Liatsis. 2005. Appearance-based statistical methods for face recognition. in *47th International Symposium ELMAR-2005 focused on Multimedia Systems and Applications*. Zadar, Croatia: IEEE.

[19] Ahonen, T., A. Hadid, M. Pietika inen, and S. Member. 2006. Face Description with Local Binary Patterns:Application to Face Recognition. *IEEE Trans. Pattern Anal. Mach. Intell.* 28(12): 2037–2041.

[20] Chengjun, L. and H. Wechsler. 2002. Gabor Feature Based Classification Using the Enhanced Fisher Linear Discriminant Model for Face Recognition. *IEEE Transactions on Image Processing*. 11(4): 467–476.

[21] Luo, B., Y. Zhang, and Y.-H. Pan. 2005. Face Recognition Based on Wavelet Transform and SVM. in *IEEE International Conference on Information Acquisition (ICIA)*. The Chinese University of Hong Kong, Hong Kong: IEEE.

[22] Khansari, M., H.R. Rabiee, M. Asadi, and M. Ghanbari. 2008. Object Tracking in Crowded Video Scenes Based on the Undecimated Wavelet Features and Texture Analysis. *EURASIP Journal on Advances in Signal Processing*. 2008(1): 1–18.

[23] Turk, M. and A. Pentland. 1991. Eigenfaces for Recognition. *J. Cognit. Neurosci.* 13(1): 71–86.

[24] Jian, Y., A.F. Frangi, Y. Jing-Yu, Z. David, and J. Zhong. 2005. KPCA Plus LDA: A Complete Kernel Fisher Discriminant Framework for Feature Extraction And Recognition. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*. 27(2): 230–244.

[25] Juwei, L., K.N. Plataniotis, and A.N. Venetsanopoulos. 2003. Face Recognition Using Kernel Direct Discriminant Analysis Algorithms. *IEEE Trans. Neural Networks*. 14(1): 117–126.

[26] Cai, D., X. He, and J. Han. 2008. SRDA: An Efficient Algorithm for Large-Scale Discriminant Analysis. *IEEE Transactions on Knowledge and Data Engineering*. 20(1): 1–12.

[27] Kittler, J., M. Hatef, R.P.W. Duin, and J. Matas. 1998. On Combining Classifiers. *IEEE Trans. Pattern Anal. Mach. Intell*. 20(3): 226–239.

[28] Lajevardi, S.M. and Z. M. Hussain. 2010. Higher Order Orthogonal Moments for Invariant Facial Expression Recognition. *Digit. Signal Process.* 20(6): 1771–1779.

[29] Li, D., X. Tang, and W. Pedrycz. 2012. Face Recognition Using Decimated Redundant Discrete Wavelet Transforms. *Machine Vision and Applicatons*. 23(2): 391–401.