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Survey

Near infrared face recognition: A literature survey

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ABSTRACT

As a primary modality in biometrics, human face recognition has been employed widely in the computer vision domain because of its performance in a wide range of applications such as surveillance systems and forensics. Recently, near infrared (NIR) imagery has been used in many face recognition systems because of the high robustness to illumination changes in the acquired images. Even though some surveys have been conducted in this infrared domain, they have focused on thermal infrared methods rather than NIR methods. Furthermore, none of the previous infrared surveys provided comprehensive and critical analyses of NIR methods. Therefore, this paper presents an up-to-date survey of the well-known NIR methods that are used to solve the problem of illumination. The paper includes a discussion of the benefits and drawbacks of various NIR methods. Finally, the most promising avenues for future research are highlighted.

Contents

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1. Introduction

Among the various recognition tasks in biometric technology, face recognition (FR) has received much attention in the field of computer vision. The first research on FR was conducted in the 1950s [1] and 1960s [2] and reported in the psychology and engineering literature, respectively. Despite significant developments and substantial progress in this domain, automatic FR is still a difficult task because of the wide range of variations in human faces caused by illumination, eyeglasses, head positions and facial expressions. Hence, methods that result in highly accurate feature extraction with high robustness to variations are crucial. Because FR is a main task of the human vision system, most researchers have concentrated on FR in the visible domain [3–22]. The main drawback of these studies, however, is the high dependency of their FR systems on illumination variations and even skin color [23]. Several illumination-invariant FR methods have been proposed, which fall into two main categories: passive methods and active methods (Fig. 1) [24].

In passive methods, visible spectrum images are studied to overcome the problem caused by illumination variation. Comprehensive surveys of illumination invariant methods, especially passive methods, were reported in [25,26]. The passive method can be categorized into four groups: illumination variation modelling [27–32], illumination invariant features [18,24,33–39], photometric normalization [40–43], and a 3D morphable model [44,45]. One major drawback of this approach, however, is the loss of useful information about facial images in illumination compensation.

For active methods, active imaging techniques are employed to overcome illumination variation. These methods are used to obtain facial images of illumination-invariant modalities or to acquire facial images taken in consistent illumination conditions. Active methods can be divided into those that use 3D information [45–48] and those based on infrared [49,50]. Infrared methods can be divided into thermal infrared [51–62] and near infrared [63–72]. The major drawbacks of active methods are increased costs and the high computational complexity of systems when 3D images are used. The other drawbacks of active methods, when thermal images are employed, include their high sensitivity to environmental temperatures, health conditions and perspiration [46,73].

Recently, near infrared imagery (NIR) has been used in many FR systems because of the high robustness of NIR cameras to illumination variations and the high quality of the acquired images [74,75]. As shown in Fig. 2, the NIR band falls between the visible light band and the thermal infrared band. NIR images have a main advantage in comparison with visible images. They are entirely free from the influence of external light. Hence, NIR images taken in the dark or under low illumination are much more informative than images acquired in the visible spectrum under the same conditions (see Fig. 3) [65,74]. As a result, FR systems based on NIR imagery are more accurate than those based on visible imagery.

Many surveys of the literature on the FR domain have been conducted. In particular, surveys of FR methods were performed by [25,46,47,53,76–80]. However, these surveys mainly focused on 3D active approaches, thermal active approaches or passive approaches. Active NIR approaches were not comprehensively described and critically analysed. A more recent review of active methods based on infrared illumination was reported in [50]. Especially noteworthy in [50] is the description of the main databases of infrared facial images. Some previous studies that addressed NIR FR were also presented in [50]. Nevertheless, this study might have been much more interesting if the authors had discussed NIR methods as comprehensively as they did thermal methods.

In this paper, we present an up-to-date overview of NIR FR methods. Our focus is on NIR methods that are used to compensate the illumination problem by means of active NIR illumination. The rest of the paper is organized as follows: in Section 2, the most recent methods are discussed and analysed, and recent works on unimodal NIR are emphasized. Previous surveys of infrared FR methods are also discussed and analysed. In Section 3, the specifications of NIR databases are given. Section 4 concludes the paper.

2. NIR methods

In this section, we describe and categorize NIR methods. In the FR domain, categorization is a critical task and is usually based on the target application, online or offline systems, initial principles, and publication dates. In this paper, we categorize the NIR FR methods according to their basic principles and mathematical tools, which enable us to determine the pros and cons of various approaches. We established five categories: (1) frequency-based methods; (2) LBP methods; (3) moment-based methods; (4) orientation-based methods; and (5) appearance-based methods (Fig. 4). Table 1 provides a chronological record of the selected methods. Our survey deals only with face recognition techniques, in which the system detects the location of the face in the image. If this is not the case (e.g., if the image contains several faces and/or other objects in unknown positions), the image must be preprocessed by using a face detection algorithm. Although face detection algorithms are beyond the scope of this paper, one was designed particularly for NIR images in [81].

2.1. *Frequency-based methods*

The first method in this category was used by Wen-Hung et al. [82]. In this study, frequency-based methods were used to correct and enhance NIR images. The problem of an artefact created in the process of NIR image formation was addressed, and an effective approach was introduced

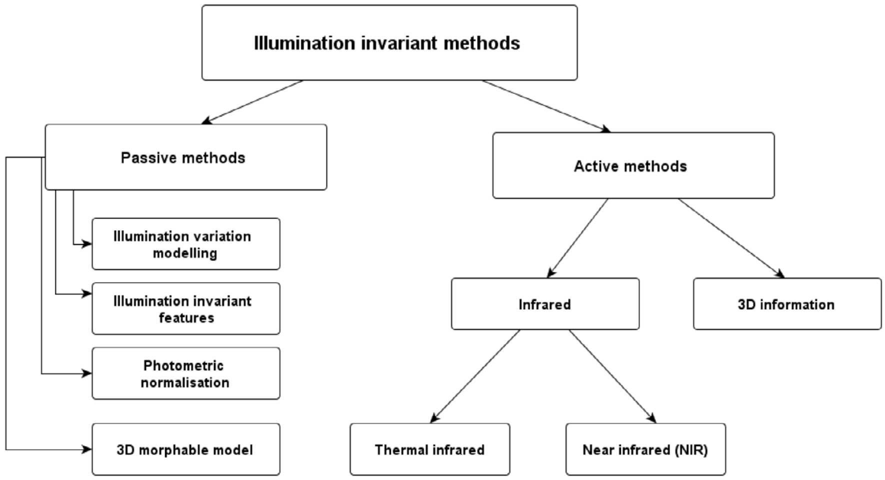

Fig. 1 – Categorization of illumination invariant methods.

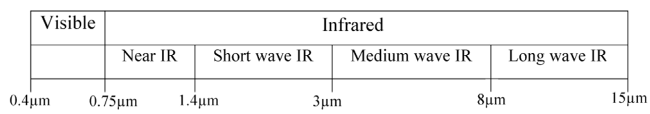

Fig. 2 – Radiation spectrum ranges.

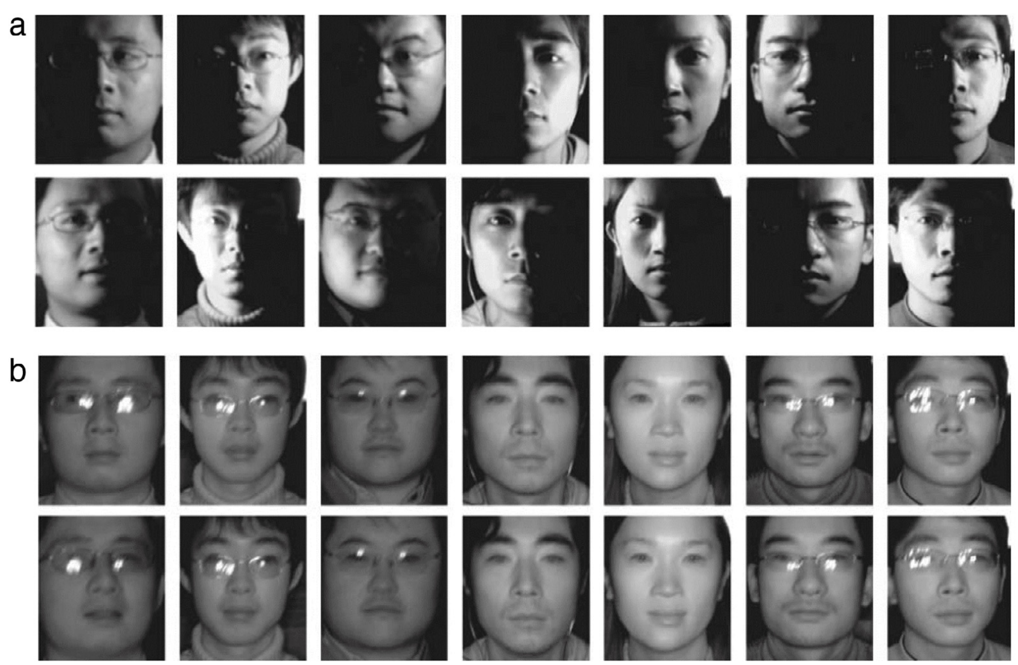

Fig. 3 – (a) Visible images in the presence of illumination variations; (b) corresponding NIR images [64].

to overcome this deficiency. In the proposed method, first, the illumination component of the image was separated by applying a Fourier transform. The result was a frequency-based representation of the input image. Because most illumination variations affect low-frequency components, homomorphic filtering was then applied to reduce the inhomogeneous NIR lighting by filtering the low-frequency component. Finally, a Gaussian high-pass filter was used to amplify the high frequencies of the resulting image. The analysis was based on different parameters of the homomorphic filter, and the experimental results showed the effectiveness of the proposed method. The study concluded that an accurate and illumination invariant FR system based on NIR images could be proposed and developed. One

Table 1 – NIR FR methods ordered chronologically.

Year	Method	Authors
2003	Fourier transform—Homomorphic filter-Gaussian filter	Wen-Hung et al. [82]
	Spectral reflectance vectors	Pan et al. [63]
2005	Local binary pattern—AdaBoost	Li et al. [74]
	Discrete cosine transform—Support vector machine	Zhao et al. [65]
2006	Local binary pattern—AdaBoost	Li et al. [83]
2007	Local binary pattern—AdaBoost	Li et al. [64]
	Sub-window local binary pattern histograms—AdaBoost	Ke et al. [84]
	Extended local binary pattern—AdaBoost	Huang et al. [85]
2010	Discrete wavelet transform—Two-dimensional principal component analysis	He et al. [86]
	Gabor Filter—Directional binary code	Zhang et al. [87]
2012	Face pattern word—Face pattern byte	Zheng [88]
	Directional binary code—Discrete wavelet transform	Jagadeesh et al. [89]
2013	Zernike moments—Spectral regression discriminant analysis	Farokhi et al. [66]
	Kernel discriminative common vector	Qiao et al. [90]
2014	Comparison study based on moments	Farokhi et al. [91]
	Comparison study based on moments, wavelets and other methods	Farokhi et al. [92]
	Zernike moments—Undecimated discrete wavelet transform	Farokhi et al. [67]
	Eigenface method	Sellami et al. [93]
2015	Zernike moments—Hermite kernels	Farokhi et al. [94]

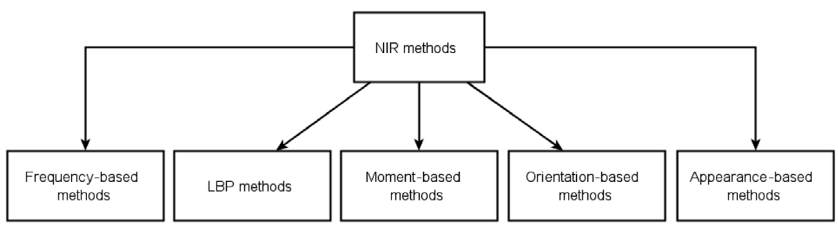

Fig. 4 – Categorization of the NIR methods according to their basic principles and mathematical tools.

Fig. 5 – Result of eye localization by the method proposed in [65].
Source: **Reprinted from [65].**

question that needed to be addressed, however, was whether the resulting NIR images could be used in FR systems. Another problem with this study is that it failed to test the resulting images in the presence of illumination changes. Hence, the superiority of NIR images over visible images in the presence of illumination changes was not highlighted.

An automatic, low-cost NIR FR system for access control was proposed in [65]. Simplified hardware was used to obtain stable illumination conditions and capture NIR images with a ‘bright pupil’ effect. An eye localization method based on the bright pupil effect was proposed, which segments the facial region and aligns and normalizes it according to the position of the eyes (Fig. 5). Discrete cosine transform (DCT) and support vector machines (SVM) were used for feature extraction and classification, respectively. Three experiments were conducted in this study. The first experiment tested the performance of eye localization in 300 images; an accuracy of 87.7% was obtained. The second experiment tested the performance of FR when face detection and cropping were done manually. A recognition accuracy of 96.15% was achieved with 250 facial images. The third experiment tested the performance of the automatic FR system; an accuracy of 79.6% accuracy was obtained with 500 images. Although the first two experiments performed above 85%, the results of the third experiment were significantly worse. Hence, the results indicated that the performance of the system depends on the accuracy of eye detection and cannot represent high accuracy in automatic FR systems. Moreover, the proposed eye detection method assumed that bright pupils are present in the eyes and that detection can be conducted simply by using the proposed method. The main drawback is that the bright pupils of narrow eyes can be occluded by the eyelids and when the eyes are closed or looking to one side. In addition, bright pupils can be affected by the specular reflections of NIR lights on faces with eyeglasses.

The performances of frequency-based methods, other feature extractors and dimension reduction methods in the NIR domain were evaluated in [92]. Radon transform + discrete

Fig. 6 – Some samples of NIR-filtered images.
***Source:* Reprinted from [74].**

cosine transform (RDCT), Radon transform + discrete wavelet transform (RDWT), Zernike moments (ZM), and independent component analysis (ICA) were employed as global feature extractors and local binary pattern (LBP), Gabor wavelets (GW), discrete wavelet transform (DWT), and undecimated discrete wavelet transform (UDWT) were used as local feature extractors. For the evaluation of dimension reduction methods, principal component analysis (PCA), kernel principal component analysis (KPDA), linear discriminant analysis + principal component analysis (Fisherfaces), kernel Fisher discriminant analysis (KFD) and spectral regression discriminant analysis (SRDA) were employed. The most common FR challenges, such as eyeglasses, facial expressions, head position, misalignment and image noise, were tested in the experiments by using the CASIA NIR database and the PolyU NIR face database. The results showed that ZMs as a global feature extractor, UDWT as a local feature extractor and SRDA as a dimension reduction method had the best performances among other methods. In addition, it was concluded that both global and local features were necessary in proposing an accurate FR method. The key drawback of this study is that a method based on local and global feature extractors was not presented, and the study focused on comparing existing methods rather than exploring a new feature extraction method.

2.2. LBP methods

Local binary patterns (LBP) were first described in 1994 in the texture spectrum model. A powerful feature, it has been used in many applications such as FR systems. In this section, the methods based on LBP in the NIR domain are discussed and their drawbacks are highlighted in detail.

A highly accurate NIR FR method was proposed in [74] for cooperative user applications. Two main contributions were made by this study. The first contribution was the novel design of the hardware device, which was equipped with NIR light-emitting diodes (LEDs) and a long pass optical filter. The LEDs on the camera lens provided appropriate active frontal lighting, and the long pass optical filter cut off visible light (<700 μm) while allowing NIR light (850 μm) to pass. As a result, not only was appropriate active frontal lighting provided by the proposed imaging hardware but also lighting from other sources was also minimized. Examples of the images are shown in Fig. 6. The second contribution of [74] comprised two learning-based algorithms: learning for face/eye detection and learning for face-based detection on an LBP histogram. To cope with the complex classification, the AdaBoost learning procedure was proposed, which made the system suitable for real-time systems. The proposed system was evaluated in time-attendance and access-control applications. Given the false alarm rate of 10^{-7}, an overall detection rate of 96.8% was reported for face detection. In the case of various indoor locations and different illumination conditions (even total darkness), less than 0.3% was reported as an equal error rate of the proposed system. A major drawback of this proposed system is its deficiency in outdoor applications. A much more systematic study would identify the performance of face detection when eyeglasses are used. In addition, a further study could compare the detection rate of the proposed method with state-of-the-art face detection methods, such as Viola and Jones, by using NIR images (i.e., invisible images).

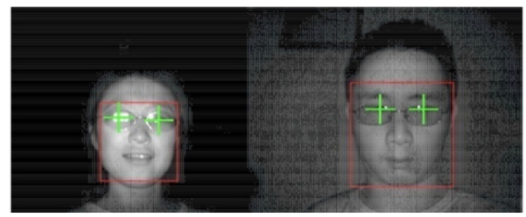

Fig. 7 – Examples of eye and face detection of NIR images with eyeglasses.
***Source:* Reprinted from [83].**

An NIR image-based FR system was introduced in [83]. The contributions of this study included new designs for an image capture device and learning-based methods. The learning-based methods were the same as proposed by Li et al. [74]. Moreover, the system evaluation and the results were similar to [74]. The main difference in the research was that the concept of LBP and the process of eye detection were discussed in detail. Significantly, face images with eyeglasses were included in the face detection process (Fig. 7). The results showed a 90%-verification rate (VR), a false acceptance rate (FAR) = 0.001, as well as a 95% VR at FAR = 0.01 for FR evaluation and a 0.3% equal error in the system evaluation. The results were based on evaluating the speed of the system in detecting the face and eyes in a 640 × 480 image: 32.3 ms per frame on a P4 3.0 GHz PC. In addition, the speed of the matching engine in the FR process was 56 ms per frame in a database of 1000 persons with five images per subject. These results showed that the proposed system ran very quickly and could be applicable to real-time FR systems. The main drawback of the proposed system, however, was the low performance of the features extracted by LBP according to head position, noise and misalignment. The study would

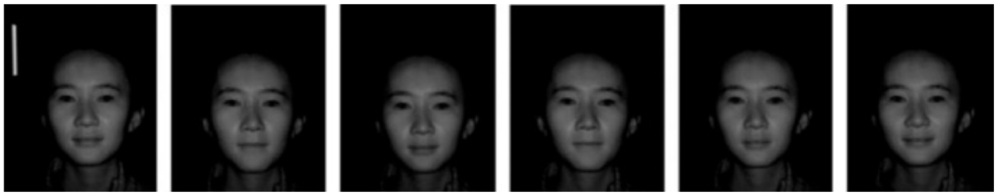

Fig. 8 – NIR images taken by the proposed NIR imaging system.
***Source*: Reprinted from [64].**

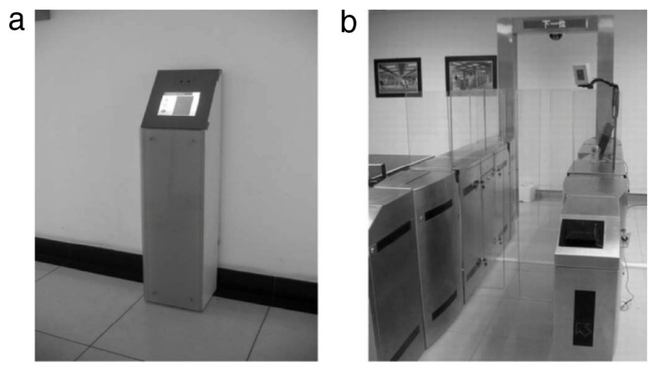

Fig. 9 – (a) Time attendance and access control system; (b) machine readable travel document (MRTD) system.
***Source*: Reprinted from [64].**

have been far more convincing if the author had extended the proposed system to outdoor applications.

Li et al. [64] introduced a highly accurate illumination invariant FR system in the NIR domain. In this study, a new hardware based on active NIR imaging system was designed to produce front-lighted face images (Fig. 8). An accurate method based on LBP features and statistical learning methods was proposed to compensate the illumination problem. A significant result was that the proposed accurate face and eye detection method dealt with eyeglasses as well as illumination variations in facial images. The entire system was simulated for access control, time attendance, and a machine-readable travel document (MRTD) system (Fig. 9). Seven experiments were conducted to evaluate the system. In the first test, the accuracy of the proposed face and eye detection was evaluated: given that FAR $= 10^{-7}$, a 98% face detection rate was achieved with a speed of 18 ms per frame; given that FAR $= 10^{-2}$, 98% and 87% eye detection rates were obtained for eyes-without-glasses and eyes-with-glasses at a speed of 25 ms per frame, respectively. In the second experiment, the proposed FR was evaluated. At FAR $=$ 0.1%, a verification rate of 91.8% was obtained. In the third and fourth experiments, the performance of the proposed FR in producing images despite different challenges included eyeglasses versus no-eyeglasses and time lapses. At FAR $=$ 0.1%, verification rates of 87.1% and 83.24% were achieved for the eyeglasses versus no-eyeglasses and time-lapse challenges respectively. In the fifth experiment, NIR and visible images under weak illumination were compared, and the superiority of NIR images over visible images under weak illumination was highlighted. In the sixth experiment, the proposed system was evaluated for access-control and time-attendance applications. An error of 0.3% or less was obtained using the proposed system. Finally, the performance of the system was investigated by using the faces of Africans and Caucasians, which were categorized into different ethnic groups. It was concluded that the accuracy of system was not affected by using ethnically different faces. A major drawback of this approach, however, was the deficiency of the feature extraction method (LBP features) in the presence of head position, noise and misalignment [92,95,96]. Moreover, as noted by the authors, their approach would be unsuitable in uncooperative user applications and in outdoor applications.

Following the previous research in [64], partially based FR using NIR images was proposed in [84] to improve the performance of the previous methods in the presence of head position variations. The active NIR imaging hardware and the captured images were the same as in the previous study. Examples of the captured images are shown in Fig. 10. In the proposed method, an NIR face image was decomposed into different facial parts, including the nose, eyes mouth and their combinations. To maintain the global information and enhance the discrimination power of the system, the entire face was also considered as one facial part. A classifier was then built for each part by using sub-window local binary pattern histograms (SLBPH) features boosted by AdaBoost learning. Finally, three fusion rules – the max rule, sum rule and LDA-based sum rule – were used to fuse the outputs of the part classifiers. The study generated 3237 images of 35 persons. The proposed method and the previous holistic method [64] were compared, which resulted in recognition rates of 96.03% and 91.5% (with FAR $=$ 0.1%) in the proposed method and previous holistic method, respectively. Accordingly, the results showed that the proposed part-based method with LDA-weighted sum rule outperformed the previous method [64] by 4.53%. However, a serious weakness of this study was that no comparison was made between the proposed method and other conventional methods. Another problem with this approach was that it failed to report the speed of the proposed system. Hence, one question that needs to be addressed is whether the proposed system could be used for automatic real-time systems or not.

Huang et al. [85] introduced a novel NIR FR method based on extended local binary pattern (ELBP) to solve the problems caused by illumination variations. In the proposed method, each NIR image was divided into local parts (Fig. 11) and then local features were extracted by an ELBP operator. As soon as the local features were extracted, they were concatenated to form a global feature vector. The AdaBoost algorithm then was used as a dimension reduction to select the most representative features. Two experiments based on NIR and FERET databases were conducted to evaluate the system. In the first experiment, the NIR database was used, and the performance was compared to other conventional methods, including PCA, LDA and LBP. The results showed that ELBP, which had an accuracy rate of 95%, had the best performance. It was concluded that ELBP was more effective than LBP for NIR FR because of its ability to extract a greater number of discriminative features. In the second experiment, the performance of ELBP was evaluated using the FERET database. The best results of FERET 97, LBP, and ELBP were compared. The results showed that ELBP had the lowest accuracy. Based on the results, it was concluded that the proposed FR method based on ELBP could not be used to derive visible images because of the dramatic change in the grey value differences of the neighbouring pixels in these images. One major drawback of this study was that the challenges were limited to moderate facial expressions and head positions, and the proposed FR system was not evaluated for facial images with misalignments, noise and eyeglasses.

2.3. Moments-based methods

Moments-based methods are the most commonly used to obtain positive results in FR systems. In these methods, the image is projected onto certain basic functions, and then the projected image is calculated by integration. Particularly important is that the acquired features are much more robust to noise and similar factors. However, the main drawback of moments-based methods is that a local change in the image will cause big changes in the values of the global features [97]. Hence, they cannot be used when occlusion occurs. In this section, moments-based methods are discussed.

Farokhi et al. [66] presented a noise and rotation invariant NIR FR system based on ZMs and SRDA to cope with head rotation (in-plan rotation), noise, facial expression and slight poses. Five experiments were conducted. In the first experiment, the parameters were set. It was concluded that ZMs in the order of 10 and SRDA with a regularization parameter of 0.01 gave the best recognition accuracy. Hence, these values were chosen for further experiments. In the second experiment, performance evaluations were done for images with facial expression and slight head positions. The Fisherfaces method, LBP + Fisherfaces (LBPF), wavelet transform + 2DPCA (W2DPCA), and ZM + Fisherfaces were used for comparison. An accuracy of 99.5% was obtained with four images in the training set, which showed the effectiveness of the proposed method. In the next experiment, the rotation invariance in the proposed method was investigated. The absolute values of ZMs were used as features, and different angles from 0 to 150° were tested. The results showed the rotation invariance property of features using ZMs. In the fourth experiment, the robustness of the proposed FR method against salt-and-pepper noise was tested. An accuracy of 98.2% was achieved when the noise density was 0.1. The accuracy of W2DPCA, Fisherfaces, LBPF and ZMF were reported as 80.4%, 87.7%, 72.3% and 92.5%, respectively. Finally, the computation time of the proposed method was measured and compared with other methods. It was concluded that the proposed method had the potential to be implemented in real-time FR systems. The most important limitation of the proposed method was that the features extracted by ZMs were very sensitive to occlusion, which could have been caused by eyeglasses because of the global nature of the resulting features.

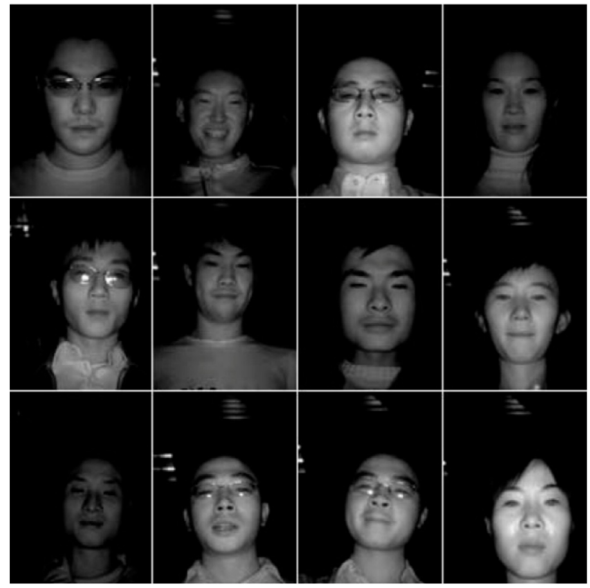

Fig. 10 – Samples of NIR images used in the study [84]. ***Source:*** **Reprinted from [84].**

To investigate the performance of various types of moments in the NIR domain, a comparative study of moments-based feature extraction methods was conducted in [91] to determine their capability of recognizing facial images with different challenges. Geometric moments (GMs), Zernike moments (ZMs), pseudo-Zernike moments (PZM), and wavelet moments (WM) were used for the evaluations. Two experiments were conducted in this study. In the first experiment, the performance of moments-based feature extraction methods using facial images with head positions and facial expressions were investigated. The recognition rates of GMs, ZMs, PZMs and WMs were reported as 85.57%, 92.21%, 90.41%, and 82.21%, respectively, using the CASIA NIR database with three images in the training set. In the second experiment, the robustness of the different moments to Gaussian white noise was tested. Recognition rates of 52.55%, 82.16%, 78.31% and 61.47% were obtained by GMs,

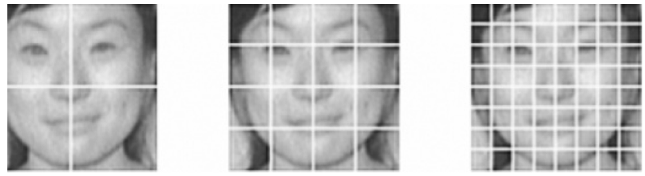

Fig. 11 – Division of NIR images to local regions.
***Source:* Reprinted from [85].**

ZMs, PZMs, and WMs, respectively, when the signal-to-noise ratio (SNR) was 21. Based on the results, it was concluded that in discrimination power and noise immunity, the ZMs performed the best among the other moments. Moreover, it was shown that the superiority of PZMs to ZMs in the presence of noise was not true in general. The most important limitation of this study was that the authors only compared moments-based methods; however, many other approaches may perform even better than the best moments-based methods in some situations.

Following the previous research conducted in [92], an accurate NIR FR method using global and local features was presented in [67]. This method coped simultaneously with most of the common challenges. In the proposed method, ZMs and undecimated discrete wavelet transform (UDWT) were used to extract global and local features, respectively. SRDA was then applied to reduce the dimensions of the features to obtain the most discriminative. Finally, a dynamic decision fusion method was proposed to combine the global and local features accurately and balance their importance by assigning dynamic weights. The main contributions of this study was that the comprehensive experiments, the comparison study and the analysis were conducted in the presence of the most common changes in NIR domain. To improve the performance, parameters were set in the first part of the experiment. The order of ZMs, the value of regularization of SRDA, the levels of decomposition in UDWT and the wavelet basis of UDWT were set empirically at 10, 0.01, 3 and 'Db3', respectively. When the parameters were specified, the experiments were conducted. Local binary pattern (LBP) + Fisherfaces (LBPF), principal component analysis (PCA), kernel principal component analysis (KPCA), linear discriminant analysis (LDA), orthogonal locality preserving projection (OLPP), pseudo Zernike moments (PZM) + radial basis function neural network (PZMRBF), and decimated redundant discrete wavelet transform + Fisherfaces (DRDWTF) were used in the comparison. The CASIA NIR database and the PolyU NIR face database (PolyU-NIRFD) were utilized to obtain data for the experiments. Recognition accuracies of 96.58%, 98.50%, 85.82% and 99.75% were obtained for images in the CASIA NIR database in the presence of images with eyeglasses, facial expression, head rotation in x-axis, and Gaussian noise, respectively (SNR $= 21$). Recognition accuracies of 97.58% and 54.01% were obtained for images in the PolyU-NIRFD with facial expressions and head rotation in the y-axis, respectively. The proposed method achieved the best performance in both databases. Another experiment was conducted to measure the accuracy of the method in the presence of misalignments. In the presence of translation less than 2 pixels in each direction, rotation up to $+/-3$ degrees, scaling from 0.95 to 1.05, and mixed misalignments, the results showed 99.51%, 98.11%, 99.46%, and 96.80%, respectively, which were the best performances among other methods. Finally, the time complexity of the mentioned FR methods were measured and compared. It was shown that the time complexity of the proposed FR method was higher than that of the other methods. It was concluded that the complementary information provided by both global and local features considerably enhanced the discrimination power of the FR system. The main limitation of the proposed method was that the UDWT used in the feature extraction was not very efficient in terms of memory usage and computational time.

An enhanced NIR FR method based on ZMs and Hermite kernels (HK) was introduced in [94] to cope with eyeglasses, facial expression, head position, scale and time lapse. The proposed method was the same as the method (ZMUDWT) previously introduced in [67]. However, its main target was to decrease the time complexity in the previous method while maintaining the recognition accuracy. Hence, ZMs were used again as the feature extractor in the global part, and UDWTs were replaced by HKs in the local part. Finally, a principal component analysis (PCA) and then a linear discriminant analysis (LDA) were conducted to generate discriminative features. The accuracy of the method was compared with other FR methods, including Gabor wavelet + Fisherfaces LDA, LBP + LDA (LBPL), Gabor wavelet + DBC (GDBC), wavelet Scattering (WS) and ZMs + UDWT (ZMUDWT), in images with the most common challenges. Recognition accuracies of 91.47% and 87.22% were acquired using the CASIA NIR database and the PolyU NIR face database, respectively. The results indicated that the usage of HKs instead of UDWT not only enhanced the accuracy of the previous method (ZMUDWT) but also decreased the time complexity of the system. Hence, the proposed ZMHK method was the best among the tested methods.

The high performance of ZMs in comparison with other methods was investigated in [92], which was already mentioned in Section 2.1.

2.4. Orientation-based methods

During the last two decades, orientation-based methods have been widely used in image processing, particularly in multi-resolution analysis. In these methods, an input image is decomposed in bands that include different information about it. In this section, orientation-based methods are discussed and analysed.

An NIR FR method based on combination of wavelet transform (WT) and two-dimensional principal component anal-

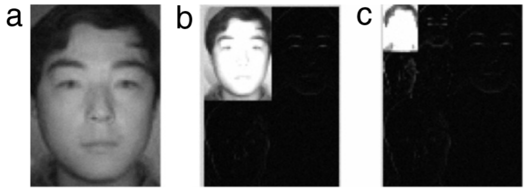

Fig. 12 – Wavelet decomposition of NIR image: (a) original face image; (b) decomposed image at depth one; (c) decomposed image at depth two.
Source: **Reprinted from [86] with permission.**

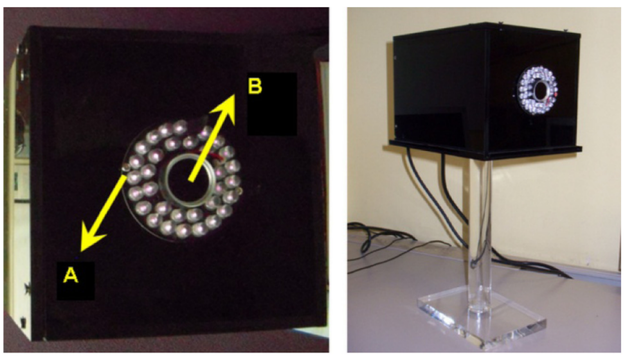

Fig. 13 – The NIR image acquisition device. 'A' and 'B' are the NIR LED light source and the NIR sensitive camera equipped with NIR filter, respectively.
Source: **Reprinted from [87].**

ysis (2DPCA) was proposed in [86]. In the proposed method, an NIR image was decomposed by WT to low frequency and high frequency subbands (Fig. 12). Then 2DPCA was applied on low frequency subbands to extract the features. To improve the recognition rate, a best-depth analysis and a best-basis analysis were conducted. The results showed that the highest accuracy was achieved when the wavelet decomposition depth was 2 and the wavelet basis was 'DB4'. Finally, the performance was evaluated was by using 300 NIR images of 30 persons. PCA, 2DPCA, and WT + PCA were used for the comparison. Recognition rates of 74%, 89.33%, 84.67%, and 92% were obtained by PCA, 2DPCA, WT + PCA, and WT + 2DPCA (proposed method), respectively, showing that the proposed method was an effective technique in NIR FR. A major drawback of this approach was that the translation variant of WT was used in the proposed method, which may have decreased the accuracy of the system because of the dramatic change in wavelet coefficients in the presence of translation [98,99]. Moreover, the proposed system was limited to the usage of the low-frequency component, which is sensitive to occlusion, and the effectiveness of the high-frequency subbands was neglected. Another problem with this approach is that state-of-the-art methods were not used in the comparisons, which were limited to two simple methods. A further study could examine the performance by using a large database and a variety of challenges.

Zhang et al. [87] proposed a new feature extraction method, directional binary code (DBC), which encodes directional and spatial information about facial images. Especially interesting was the design of an NIR face image acquisition device (Fig. 13) and the introduction of a big NIR facial database (35,000 images), which included most FR challenges (Fig. 14). In this method, an image was divided into four sub-blocks. Then Gabor filtering was used to enhance the image features. Finally, DBC was applied to code the features that were enhanced by Gabor filtering. The DBC feature maps of an NIR image are shown in Fig. 15. Four experiments were done in this study. In the first, second, and third experiments, different datasets of NIR images were used for the evaluations. The study compared LDA, PCA, Gabor-LDA, Gabor-PCA, LBP, DBC, Gabor-LBP, and Gabor-DBC (proposed method). The results showed that Gabor filtering greatly enhanced the discrimination of the features. The best accuracy was reported in the first experiment at 97.6%, which was the highest of all other methods in the experiments. In the last experiment, the performance evaluations were conducted using the FERET database. In this experiment, DBC was compared with LBP. The results showed that the DBC outperformed LBP method in the Fb, Fc, Dup1 and Dup2 gallery sets of the FERET database. A limitation of this study was that the authors did not consider noise and misalignments in the experiments, which were introduced as the biggest challenges of FR systems [100].

Zheng [88] introduced an orientation-based NIR FR method. In the proposed method, first Gabor wavelet transform (GWT) was applied on a normalized face image to extract facial features. Multiple-band orientational codes were then put into a face pattern byte (FPB) or a face pattern word (FPW) pixel-by-pixel. A visualization of FPB is shown in Fig. 16. The ASUNIR, ASUDC and ASUIR databases were used for the performance evaluation, which included NIR images, visible images and thermal images, respectively. LDA, PCA, and elastic bunch graph matching (EBGM) were used in the comparison. The results showed that the NIR face image database had the best performance results compared with the other two face image databases. Moreover, the FPW method, with verification rates of 98.43%, 97.28% and 93.06%, achieved the best performance among other methods that used the ASUNIR, ASUDC, and ASUIR databases, respectively. A major drawback of this approach was that the proposed methods were not tested on a large database, and they were not compared with similar methods such as LBP, ELBP or DBC. In addition, the specification of the images in the NIR database was not discussed in detail.

DBC-based FR using DWT was proposed in [89]. This study was conducted to increase the accuracy of DBC, which was presented in [87]. In this proposed method, an input image was first decomposed by DWT with a 'Haar' wavelet up to depth 1, and the LL subband was considered. The generated LL subband was then partitioned into 100 cells sized 5×5. The directional binary code (DBC) was then applied on each 5×5 partition to derive the features. The Euclidean distance was used for the classification. The PolyU NIR face database was used for the evaluation, and the proposed DBC method was compared with the existing Gabor-DBC method [87]. A recognition rate of 98.8% was achieved by the proposed method, whereas the recognition rate of Gabor-DBC (GDBC) was reported at 97.6%. One question that needs to be addressed, however, is whether the 1.2% enhancement in recognition rate was statistically significant or not. As the results showed,

Fig. 14 – Samples of PolyU near infrared face database (PolyU-NIRFD).
***Source*: Reprinted from [87].**

Fig. 15 – Example of directional binary code (DBC) feature maps: (a) original NIR image; (b) DBC feature maps along directions at 0°, 45°, 90° and 135°.
***Source*: Reprinted from [87].**

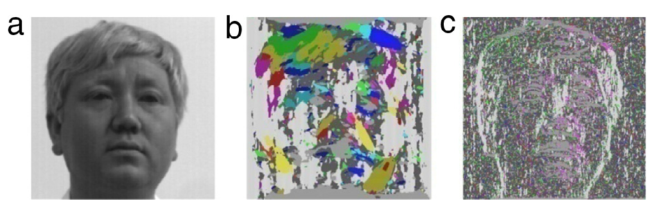

Fig. 16 – (a) Original NIR image (b)–(c) low and high half-byte of FPB features, respectively.
***Source*: Reprinted from [88] with permission.**

the recognition accuracy was improved by increasing the number of partitions from 4 (GDBC) to 100 (proposed method). We believe that the number of image partitions should be balanced between time complexity and recognition rate, which was not considered in this study. In fact, increasing the number of partitions may have led to high computational complexity, which is neither justifiable nor necessary because the complexity rate is essential in real-time FR systems. Another drawback of this approach is the deficiency of the proposed caused by the use of DWT in the proposed feature extraction method.

The performance of discrete wavelet transform, undecimated discrete wavelet transform, Hermite kernel, and wavelet scattering as orientation-based feature extractors in the NIR domain were studied in [67,94], which are discussed in detail in Section 2.3.

2.5. *Appearance-based methods*

Appearance-based methods are well known and widely implemented in FR systems. In appearance-based methods, an image is projected into subspace, and the closest pattern is found accordingly. In these methods, all pixels in the entire facial image are taken as a single vector, and then the relevant features with important information are extracted and used for classification. In this section, some appearance-based methods in the NIR domain are reviewed.

The usefulness of NIR hyperspectral images for FR in the presence of facial expression and head position was investigated in [63]. In this study, hyperspectral images were taken using 31 spectral bands with centre wavelengths separated by 0.01 μm over the NIR (0.7–1.0 μm) with a spatial resolution of 468×494 (Fig. 17). In the first part of the experiments, it was shown that the spectral information in the NIR images had good discrimination power and relative stability over time. Hence, 200 subjects (seven images per subject) of diverse sex, age and ethnicity were participants in the subsequent experiments, which used spectral information about facial tissue for recognition. The results showed that the proposed method had good recognition performance over time in facial images with head positions and facial expressions. One question that needs to be asked, however, is whether the proposed method could be used for outdoor and automatic FR or not. Moreover, the experiments were limited to the challenges of head positions and facial expressions; however, noise and eyeglasses, which occur in uncooperative FR systems, were not considered in the experiments. In [101], this work was extended to multi-spectral appearances instead of a sparse set of local features. Although the same database was used, improved performance was reported.

An FR system based on the NIR imaging system (ANIRIS) was proposed in [90]. The kernel discriminative common vector (KDCV) and the radial basis function (RBF) neural network were employed for feature extraction and classification, respectively. Two experiments were conducted to evaluate the

Fig. 17 – Samples of hyperspectral images of one subject (31 bands).
***Source:* Reprinted from [63].**

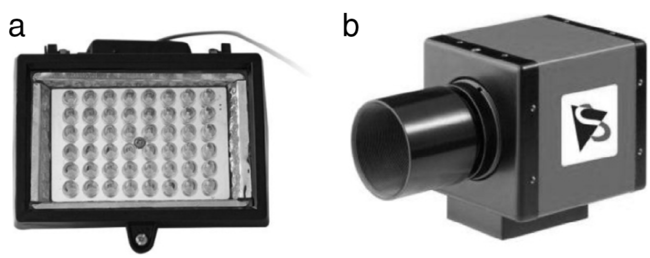

Fig. 18 – Two main pieces of the hardware used in the capture device system: (a) illuminator (b) Imaging Source DMK 21AU618 camera.
***Source:* Reprinted from [93] with permission.**

proposed method. In the first experiment, the NIR radiations from the light source and the environment were compared. The results showed that changes in illumination had very little influence on the NIR images. Hence, the usage of NIR images was justified. In the second experiment, three collections were used, including visible images, NIR images of HITSZ Lab2, and a combination of HITSZ Lab2 and self-built EEINIR face database images. The results showed that the experiments based on visible images under varying illumination had low recognition rates, whereas the experiments based on the NIR images had high accuracy (95%). It was concluded that active NIR imaging coped with illumination variations and enhanced the recognition rate of the FR system. However, the proposed method had the following drawbacks. The usage of KDCV was not justified, and its superiority to the discriminative common vector (DCV) was not described. The parameters that were used for the RBF neural network were not introduced or justified. No comparison was made between the proposed method and other state-of-the art methods. The challenges were limited to position variations and facial expressions; other challenges were not considered. One question that needs to be asked, however, is whether the proposed method would be applicable in real-time or outdoor applications.

Near infrared facial recognition utilizing OpenCV software was introduced in [93]. The goal of this study was to utilize a leading algorithm to perform NIR FR. Three main systems – an illumination device, a camera (Fig. 18) and a software suite – were examined in this study. The software suite included the image manipulation, facial detection, and FR procedures. The Viola–Jones method [102] was used for face detection, and the Eigenface method [3] was used for FR. The entire system was evaluated using visible and NIR images under two illumination conditions: 'well lit' and 'low light'. The error rates of the visible images using seven images per person were reported as 0% and 75% for well-lit and low-light illumination conditions, respectively, whereas those of the NIR images were reported as 3.57% and 0%. The results showed that the NIR images were more effective than visible images under low-light conditions. A major drawback of this approach is that the specifications of the database were not described well. In addition, the eigenface method, which is used for recognition, requires adequate training images to produce highly accurate FR. Moreover, its performance was strongly affected by the presence of noise and eyeglasses. Another limitation of this study is that it did not consider facial expressions and eyeglasses in the probe images.

The performances of well-known appearance-based methods, such as principal component analysis [3], linear dis-

Table 2 – Summary of NIR databases.

Name	Subjects	Challenges				
		Illumination	Eyeglasses	Head pose	Facial expression	Time-lapse
CASIA	197	×	•	•	•	×
PolyU	335	×	×	•	•	•
CSIST	50	•	×	•	•	×

criminant analysis [103], kernel principal component analysis [104], and orthogonal locality preserving projection (OLPP) [105] in the NIR domain in different scenarios were investigated in [67], which was discussed in detail in Section 2.3.

Because of the increasing amount of research on near infrared-based recognition, several methods are reported in the literature. These include near infrared FR at a distance [106,107]; heterogeneous FR methods that attempt to match two facial images from alternate imaging modalities, such as NIR and visible [108–117]; image fusion methods [118,119]; methods based on active differential imaging [69,70]; and others [75,115,120–125].

3. Near infrared face databases

In this section, we review the most relevant databases of NIR imagery for research purposes. We focus on databases that are public and freely available. A summary of the NIR databases is presented in Table 2.

3.1. *CASIA NIR database*

The CASIA NIR face biometrics database was compiled by the Institute of Automation, Chinese Academy of Sciences (CASIA). NIR light-emitting diodes (LEDs) were employed as active radiation sources, which are not only power-effective but also strong enough for indoor applications. A long pass optical filter was employed to block visible light and allow NIR light to pass. Examples of CASIA NIR images are shown in Fig. 19. The database includes 3940 NIR facial images of 197 subjects (20 images per subject) at a resolution of 640 × 480 in 'BMP' format. The challenges included moderate facial expressions, head position and eyeglasses. Some images did not have these challenges. The images were taken using a Homebrew camera at a wavelength of 850 μm. The database is available at: http://www.cbsr.ia.ac.cn/english/NIR_face Databases.asp upon request and it is free of charge.

3.2. *PolyU NIR face database (PolyU NIRFD)*

The Hong Kong Polytechnic University NIR Face database (PolyU-NIRFD) was developed by the Biometric Research Centre (UGC/CRC) at the Hong Kong Polytechnic University. A JAI camera with 850-μm wavelength was used to collect the images of 335 subjects (100 images per subject) at a resolution of 768 × 576 in 'JPG' format. This large-scale database includes normal images, NIR images and NIR images with facial expressions, sharp head positions, scale variations and time-lapse. Examples of these images are shown in Fig. 20. The database is freely available upon request for academic, non-commercial uses at http://www4.comp.polyu.edu.hk/~biometrics/polyudb_face.htm.

3.3. *CSIST database*

The CSIST database was released by the Harbin Institute of Technology Shenzhen Graduate School. It contains facial images captured in different illumination environments. It contains two main databases: Lab1 and Lab2. The Lab1 database contains 500 visible and 500 NIR images of 50 subjects at 100 × 80, whereas the Lab2 database contains 1000 visible and 1000 NIR images of 50 subjects at 200 × 200 in 'BMP' format. Examples of the acquired images are shown in Fig. 21. The images in Lab2 were captured under four different illumination conditions: normal illumination, left illumination, right illumination, and left and right illuminations. The facial images include variations in head position and expressions. This database is freely available for academic, non-commercial uses at http://www.yongxu.org/databases.html.

4. Discussion and summary

Near infrared (NIR) imagery in FR systems has received an increasing amount of interest because of the good performance of the acquired images under various illumination conditions. NIR images represent high-resolution images under weak illumination, which leads to accurate FR systems. This paper presents an up-to-date overview of the FR in the growing field of NIR. A summary of the performance capabilities, advantages and drawbacks of the approaches is provided. A notable limitation of most of the reviewed studies is that while each of the previous methods was accurate in the presence of special challenges, it decreased sharply in the presence of other challenges. For instance, a feature that is invariant in facial expressions or eyeglasses works well as long as misalignments or noise do not occur; otherwise, it fails considerably. The main reason is that most related works in the NIR domain have focused on the illumination problem. However, far too little attention has been paid to other challenges in FR systems, such as noise, misalignments and occlusion, which can occur in NIR FR systems. Another major drawback of the reviewed studies is that the proposed methods used mainly local features for the FR, and the effectiveness of global features was underestimated. Although local features performed well in the presence of occlusion and head position, many studies showed that a system that handles various challenges cannot be based on single features and that the fusion of local and global features could improve the performance of the system considerably. Highly accurate FR systems use both global and local features because of the generation of complementary information based on these features. Briefly, this survey revealed that is still a challenging problem to design a robust and reliable face representation that is based on both local and global features (hybrid method) in the NIR domain, which

Fig. 19 – Examples of CASIA NIR images.

Fig. 20 – Example of PolyU NIR images.

Fig. 21 – Examples of the CSIST database.

is crucial for accurate FR. We expect that hybrid methods could offer better performance than methods based on single-type features. In [67,92], good recognition rates were reported using hybrid methods for FR. In the opinion of the present authors, the results published to date show that the trends in the NIR domain are still in the early stages but have the potential for significant further improvement. We therefore make the following recommendations for further research: (i) propose an efficient feature extraction based on local and global facial features to generate complementary data types; (ii) develop accurate NIR FR at a distance; (iii) propose an effective heterogeneous FR method (visible vs. NIR); and (iv) propose multi-biometrics (face + palm vein) to enhance the performance of biometric systems in the NIR domain.

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