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A survey of palmprint recognition

Adams Kong[a,*], David Zhang[b], Mohamed Kamel[c]

[a]Forensic and Security Laboratory, School of Computer Engineering, Nanyang Technological University, Block N4, Nanyang Avenue, Singapore 639798, Singapore
[b]Biometrics Research Centre, Department of Computing, The Hong Kong Polytechnic University, Kowloon, Hong Kong
[c]Pattern Analysis and Machine Intelligence Research Group, Department of Electrical and Computer Engineering, University of Waterloo, 200 University Avenue West, Ontario, Canada

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ABSTRACT

Palmprint recognition has been investigated over 10 years. During this period, many different problems related to palmprint recognition have been addressed. This paper provides an overview of current palmprint research, describing in particular capture devices, preprocessing, verification algorithms, palmprint-related fusion, algorithms especially designed for real-time palmprint identification in large databases and measures for protecting palmprint systems and users' privacy. Finally, some suggestion is offered.

1. Introduction

The inner surface of the palm normally contains three flexion creases, secondary creases and ridges. The flexion creases are also called principal lines and the secondary creases are called wrinkles. The flexion and the major secondary creases are formed between the third and fifth months of pregnancy [36] and superficial lines appear after we born. Although the three major flexions are genetically dependent, most of other creases are not [2]. Even identical twins have different palmprints [2]. These non-genetically deterministic and complex patterns are very useful in personal identification. Human beings were interested in palm lines for fortune telling long time ago. Scientists know that palm lines are associated with some genetic diseases including Down syndrome, Aarskog syndrome, Cohen syndrome and fetal alcohol syndrome [68]. Scientists and fortunetellers name the lines and regions in palm differently as shown in Fig. 1 [30].

Palmprint research employs either high or low resolution images. High resolution images are suitable for forensic applications such as criminal detection [24]. Low resolution images are more suitable for civil and commercial applications such as access control. Generally speaking, high resolution refers to 400 dpi or more and low resolution refers to 150 dpi or less. Fig. 2 illustrates a part of a high-resolution palmprint image and a low resolution palmprint image. Researchers can extract ridges, singular points and minutia points as features from high resolution images while in low resolution images they generally extract principal lines, wrinkles and texture. Initially palmprint research focused on high-resolution images [69,70] but now almost all research is on low resolution images for civil and commercial applications. This is also the focus of this paper.

The design of a biometric system takes account of five objectives: cost, user acceptance and environment constraints, accuracy, computation speed and security (Fig. 3). Reducing accuracy can increase speed. Typical examples are hierarchical approaches. Reducing user acceptance can improve accuracy. For instance, users are required to provide more samples for training. Increasing cost can enhance security. We can embed more sensors to collect different signals for liveness detection. In some applications, environmental constraints such as memory usage, power consumption, size of templates and size of devices have to be fulfilled. A biometric system installed in PDA (personal digital assistant) requires low power and memory consumption but these requirements may not be vital for biometric access control systems. A practical biometric system should balance all these aspects.

A typical palmprint recognition system consists of five parts: palmprint scanner, preprocessing, feature extraction, matcher and database illustrated in Fig. 4. The palmprint scanner collects palmprint images. Preprocessing sets up a coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction obtains effective features from the preprocessed palmprints. A matcher compares two palmprint features and a database stores registered templates.

The rest of this paper is organized as follows: Section 2 reviews palmprint scanners and preprocessing algorithms, Section 3 lists verification algorithms, Section 4 summarizes various fusion approaches

* Corresponding author. Tel.: +65 6513 8041; fax: +65 6792 6559.
E-mail addresses: adamskong@ieee.org, adamskong@ntu.edu.sg (A. Kong).

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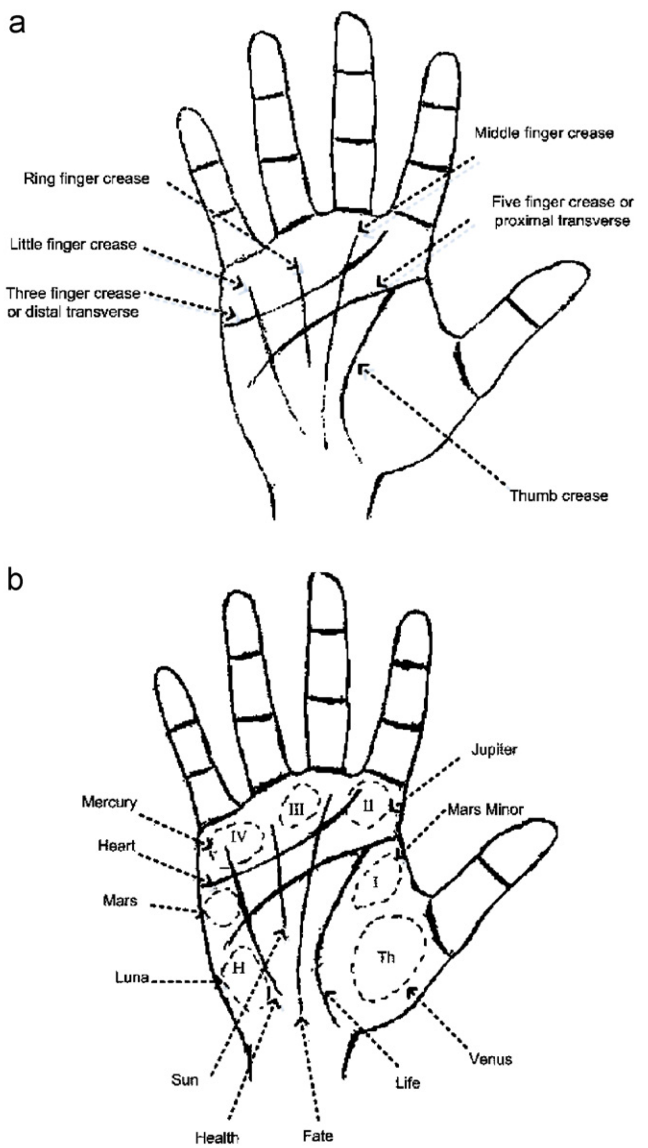

Fig. 1. Definitions of palm lines and regions (a) from scientists and (b) from fortune-tellers.

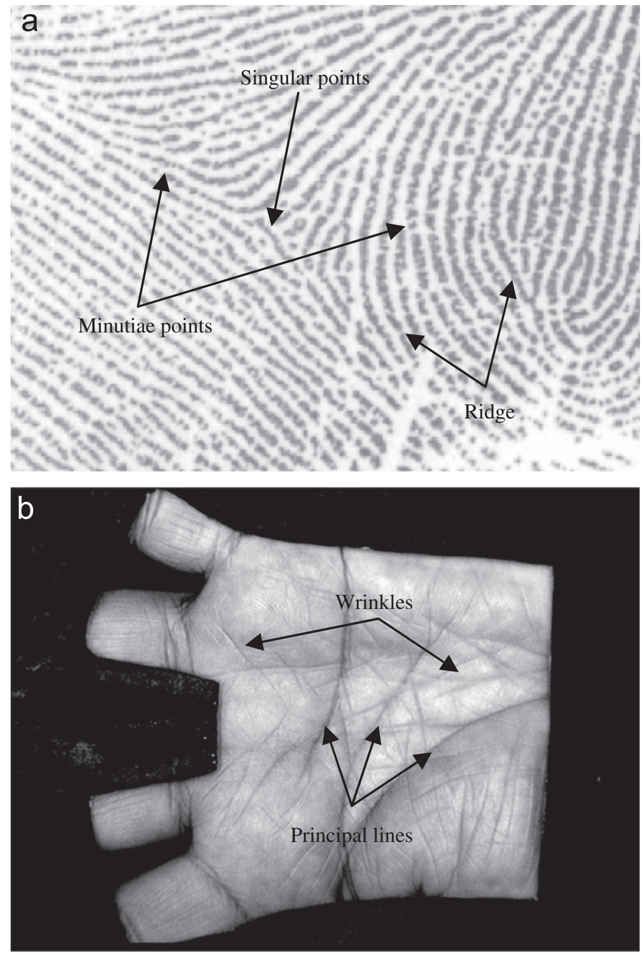

Fig. 2. Palmprint features in (a) a high resolution image and (b) a low resolution image.

for enhancing verification accuracy, Section 5 discusses the algorithms for real-time palmprint identification in large databases, Section 6 mentions the existing methods for protecting palmprint systems and user privacy and Section 7 offers some concluding remarks and further directions.

2. Palmprint scanners and preprocessing

2.1. Palmprint scanners

Researchers utilize four types of sensors: CCD-based palmprint scanners, digital cameras, digital scanners and video cameras to collect palmprint images. Fig. 5 shows a CCD-based palmprint scanner developed by The Hong Kong Polytechnic University. Zhang et al. and Han were the first two research teams developing CCD-based palmprint scanners [7,9]. CCD-based palmprint scanners capture high quality palmprint images and align palms accurately because the scanners have pegs for guiding the placement of hands [7,9]. These scanners simplify the development of recognition algorithms because the images are captured in a controlled environment. However, developing a CCD-based palmprint scanner requires a suitable selection of lens, camera, and light sources. Wong et al. provide some principles for CCD-based palmprint scanner design [93]. Although these palmprint scanners can capture high quality images, they are large.

Collection approaches based on digital scanners, digital cameras and video cameras require less effort for system design and can be found in office environments. These approaches do not use pegs for the placement of hands. Some researchers believe that this increases user acceptance. Digital and video cameras can be used to collect palmprint images without contact [37], an advantage if hygiene is a concern. However, these images might cause recognition problem as their quality is low because they collect is in an uncontrolled environment with illumination variations and distortions due to hand movement. Digital scanners are not suitable for real-time applications because of the scanning time.

Fig. 6(a) is a palmprint image collected with a CCD-based palmprint scanner and Fig. 6(b) is a palmprint image collected with a digital scanner. Although Fig. 6(a) does not include the fingers, this does not mean that CCD-based palmprint scanners cannot capture fingers. The scanner developed by Han can capture all information from a palm including fingers and palm. Capturing fingers may require increasing the size of the device. In Fig. 6(b), we can see that the palm is distorted because of contact with the scanners. This distortion does not happen in Fig. 6(a) because the scanner is better designed.

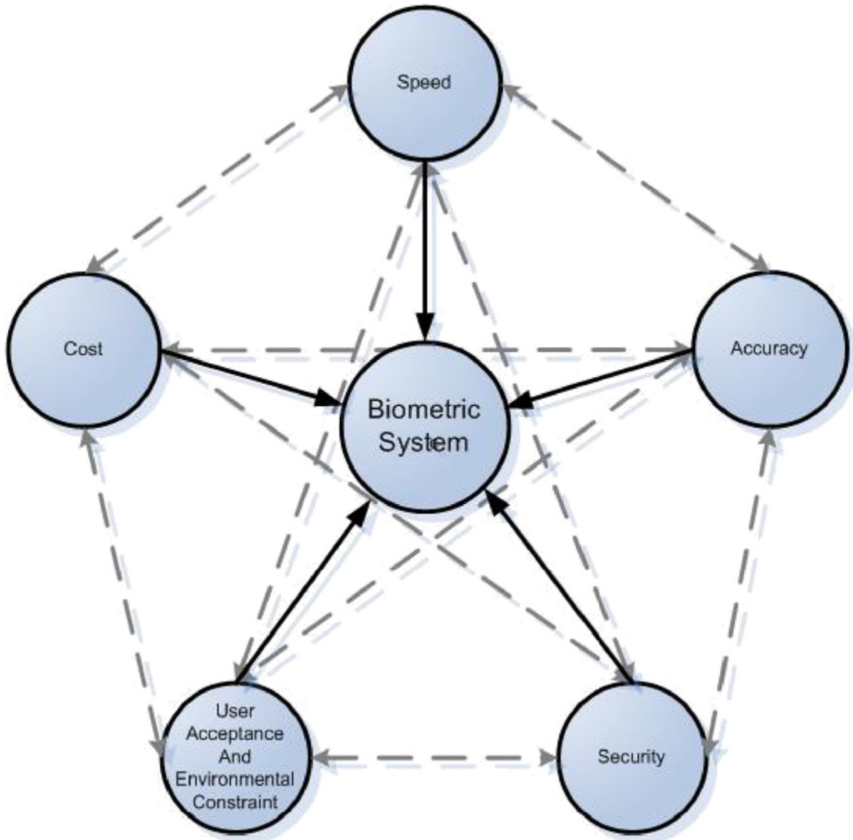

Fig. 3. The inter relationships between different objectives for designing a biometric system.

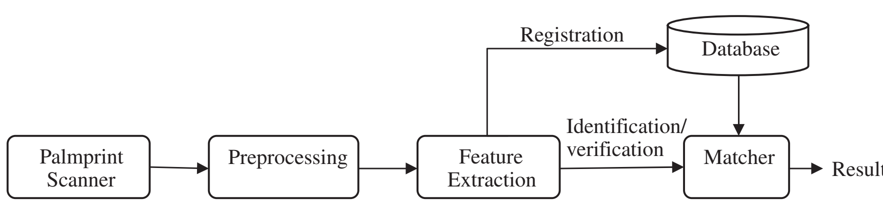

Fig. 4. An illustration of a typical palmprint recognition system.

2.2. Preprocessing

Preprocessing is used to align different palmprint images and to segment the center for feature extraction. Most of the preprocessing algorithms employ the key points between fingers to set up a coordinate system. Preprocessing involves five common steps: (1) binarizing the palm images, (2) extracting the contour of hand and/or fingers, (3) detecting the key points, (4) establishing a coordination system and (5) extracting the central parts. Fig. 7(a) illustrates the key points and Fig. 7(b) shows a preprocessed image.

The first and second steps in all the preprocessing algorithms are similar. However, the third step has several different implementations including tangent- [7], bisector- [16,48] and finger-based [9,10] to detect the key points between fingers. The tangent-based approach considers the two boundaries—one from point finger and middle finger and the other from ring finger and last finger—as two convex curves and computes the tangent of these two curves. The two intersections are considered as two key points for establishing the coordinate system. Tangent-based approaches have several advantages. They depend on a very short boundary around the bottom of fingers. Therefore, it is robust to incomplete fingers (as in the disabled) and the presence of rings. Bisector-based approach constructs a line using two points, the center of gravity of a finger boundary and the midpoint of its start and end points. The intersection of the line and the finger boundary is considered a key point. Han and his team propose two approaches to establish the coordinate system, one based on the middle finger [10] and the other based on the point, middle and ring fingers [9]. The middle finger approach uses a wavelet to detect the fingertip and the middle point in the finger bottom and construct a line passing through these two points [10]. The multiple finger approach uses a wavelet and a set of predefined boundary points on the three fingers to construct three lines in the middle of the three fingers. The two lines from point and ring fingers are used to set the orientation of the coordinate system and the line from the middle finger is used to set its position. These approaches use only the information on the boundaries of fingers while Kumar et al. proposed using all information in palms [50]. They fit an ellipse to a binary palmprint image and set up the coordinate system according to the orientation of the ellipse.

Fig. 5. A CCD-based palmprint scanner.

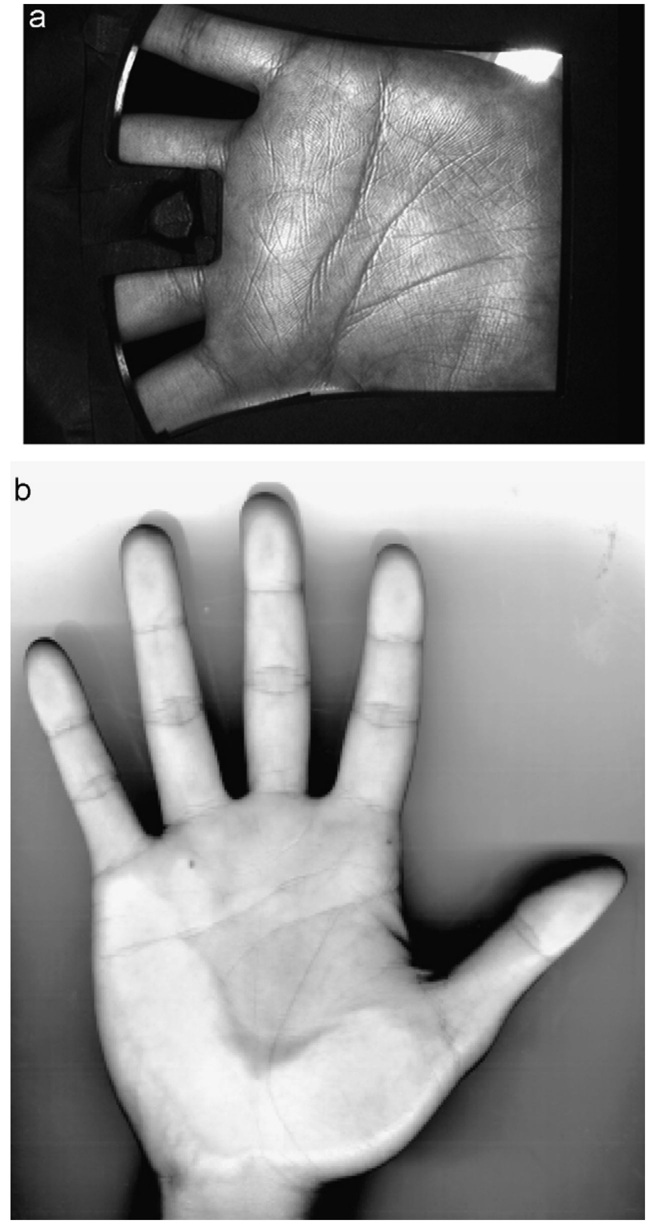

Fig. 6. Two palmprints collected by (a) a CCD-based palmprint scanner and (b) a digital scanner.

After obtaining the coordinate systems, the central parts of palmprints are segmented. Most of the preprocessing algorithms segment square regions for feature extraction but some of them segment circular [61] and half elliptical regions [41]. The square region is easier for handling translation variation, while the circular and half elliptical regions may be easier for handling rotation variation.

3. Verification algorithms

Once the central part is segmented, features can be extracted for matching. There are two types of recognition algorithms, verification and identification. Verification algorithms must be accurate. Identification algorithms must be accurate and fast (matching speed). This section concentrates on verification algorithms and identification algorithms will be discussed in Section 5. Verification algorithms are line-, subspace- and statistic-based. Some algorithms in this section can support a certain scale of identification. However, most of the researchers do not report matching speed.

3.1. Line-based approaches

Line-based approaches either develop edge detectors or use existing edge detection methods to extract palm lines [31,34,44,52,53,58–60,83,95]. These lines are either matched directly or represented in other formats for matching.

Wu et al. use Canny edge operator [103] to detect palm lines [44]. The orientations of the edge points are passed into four membership functions representing four directions. For each direction, the authors compute $E_{R,i}=\sum_{(x,y)\in R}(Mag(x,y)\times\mu_i(x,y))^2$, where μ_i represents one of the membership functions; *Mag* represents the magnitude of the lines and R is a local region. The feature value, $E_{R,i}$ is normalized. Finally, Euclidean distance is used for matching.

Wu et al. designed two masks to compute the vertical first-order derivative and the second-order derivative of palmprint images [34]. The directional first-order and second-order derivatives can be obtained by rotating the two standard marks. They use the zero-crossings of the first-order derivatives to identify the edge points and corresponding directions. The magnitude of the corresponding second-order derivative is considered as the magnitude of the lines. They retain only the positive magnitude because palm lines are valleys. The weighted sum of the local directional magnitude is regarded as an element in the feature vector. This feature is normalized by its maximum and minimum components. As with [44], Euclidean distance is used for matching.

Wu et al. propose another algorithm, which use Sobel masks to compute the magnitude of palm lines [48]. These magnitudes are projected along both x and y directions to form histograms. These histograms are considered as inputs of Hidden Markov Models (HMMs).

Boles et al. use Sobel masks and thresholds to construct binary edge images [52] and then employ Hough transform to extract the parameters of the six lines with highest densities in the accumulator array for matching.

Kung et al. formed a feature vector based on a low-resolution edge map. The feature vector is passed into decision-based neural networks [58]. This was the first paper to report an on-line palmprint recognition method.

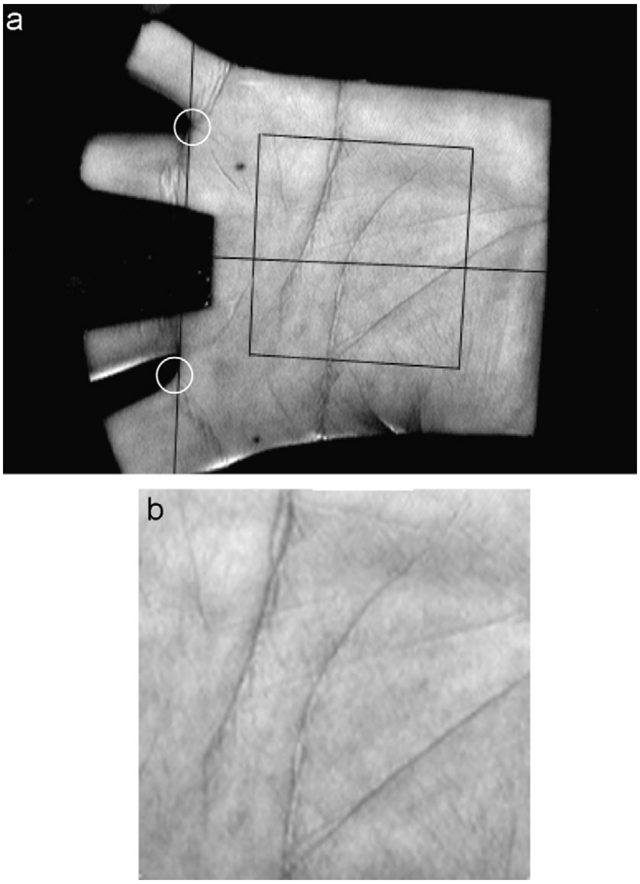

Fig. 7. Illustration of preprocessing: (a) the key points based on finger boundary and (b) the central parts for feature extraction.

Pedro et al. employ Sobel masks to enhance edge information and the statistical information in the processed images is used to estimate an optimal threshold for extracting the edges [59]. The authors then utilize a thinning algorithm to further process the edges. Several descriptors of the edges are computed as features for matching.

Huang et al. proposed a two-level modified finite radon transform and a dynamic threshold to extract major wrinkles and principal lines. Two binary edge maps are compared based on a matching scheme called pixel-to-area comparison [83]. The authors claim that the proposed algorithm has a better high false acceptance rate than a classical palmprint identification algorithm—PalmCode [1,7]. However, PalmCode still has a better at low false acceptance rate. Even though some strong wrinkles are included in the edge maps, the major features in this method are principal lines, which are genetically dependent [2].

Leung et al. employ Sobel masks to extract palm lines and line segment Hausdorff distance to compare two palmprints [95,104]. Rafael Diaz et al. use Sobel masks and morphologic operator as two separated feature extractors to obtain the gradient of the images [53]. These feature values are classified by neural networks.

3.2. Subspace-based approaches

Subspace-based approaches also called appearance-based approach in the literature of face recognition. They use principal component analysis (PCA), linear discriminant analysis (LDA) and independent component analysis (ICA) [8,12,13,18,42,63,66,67,90]. The subspace coefficients are regarded as features. Various distance measures and classifiers are used to compare the features. In

Fig. 8. The architecture of subspace approach.

addition to applying PCA, LDA and ICA directly to palmprint images, researchers also employ wavelets, Gabor, discrete cosine transform (DCT) and kernels in their methods [8,18,39,42,89,91]. Fig. 8 illustrates the architecture of subspace approach. Some researchers have developed new subspace approaches and examined them on palmprints [71–73,102,105]. Generally speaking, subspace-based approaches do not make use of any prior knowledge of palmprints. Table 1 summarizes subspace approaches.

3.3. Statistical approaches

Statistical approaches are either local or global statistical approaches. Local statistical approaches transform images into another domain and then divide the transformed images into several small regions [10,15,33,45,50,51,63,64]. Local statistics such as means and variances of each small region are calculated and regarded as features. Gabor, wavelets and Fourier transforms have been applied. The small regions are commonly square but some are elliptical and circular [29,64]. To our knowledge, no one has yet investigated high order statistics for these approaches. In addition to directly describing the local region by statistics, Wang et al. use histograms of local binary pattern as features [98]. Global statistical approaches [11,14,46,49,54] compute global statistical features directly from the whole transformed images. Moments, centers of gravity and density have been regarded as the global statistical features. Table 2 summarizes these algorithms.

3.4. Other approaches

Some approaches are difficult to classify [9,32,43,47,55,78,92,96,97,99,101] because they combine several image-processing methods to extract palmprint features and employ some standard classifiers such as neural networks to make the final decision.

Chen et al. [101] perform a two dimensional dual-tree complex transform on the preprocessed palmprints to decompose the images. Dual-tree complex transforms are proposed to resolve the weakness of traditional wavelet transform, which is not shift-invariant, for pattern recognition. Then they apply Fourier transform on each subband and regard the spectrum magnitude as features. Finally, SVM is used as a classifier.

Chen et al. extract a series of local features (e.g. average intensity) along a spiral [78] and use a time series method called symbolic aggregate approximation to represent the features and minimum distance to compare two feature vectors.

Doi et al. regard the intersection points of finger skeletal lines and finger creases and the intersection points of the extended finger skeletal lines and principal lines as feature points [55]. In addition to position information, the tangential angles between the principal lines and the extended skeletal lines are also considered as features. They used root mean square deviation to measure the differences between two features.

Han extracted seven specified line profiles from preprocessed palmprints and three fingers and used wavelets to compute low frequency information [9]. This information is formed as a new feature vector, whose dimensionality is reduced by PCA. Finally, generalized learning vector quantization and optimal positive Boolean function are used to make final decision. This work may be the first paper employing feature-level fusion for palmprint recognition.

Table 1
Summary of subspace approach.

Feature extraction	Subspace	Classifier	Ref.
Wavelets: Haar, Daubechies and Symmlet	PCA, LDA, ICA	L_1 measure	[8]
		L_2 measure Cosine measure Probabilistic neural network	
Nil	LDA	Euclidean distance	[12]
Nil	PCA	Weighted Euclidean distance	[13]
DCT	Improved Fishface	Euclidean distance	[18]
Nil	Kernel PCA	Maximum a posterior classifier	[39]
Wavelet	ICA	Euclidean distance	[42]
Nil	PCA, ICA	Euclidean distance	[66]
Nil	ICA	Radial basis probabilistic neural network	[67]
Nil	Bi-directional PCA	Assembled matrix distance metric	[71]
Nil	Kernel PCA+locality preserving projections	Euclidean distance	[73]
Gabor filter+boosting algorithm	LDA	Cosine distance	[89]
Nil	Winner-take-all network based on ICA	Radial basis probabilistic neural network	[90]
Wavelet, DCT, FFT	Kernel PCA	Support vector machine, weighted Euclidean distance, linear Euclidean distance	[91]
Nil	Unsupervised discriminant project	Euclidean, cosine measure	[102,105]

Table 2
Summary of statistical approach.

Feature extraction	Statistical feature	Shape of small regions	Classifier	Ref.
Sobel filter, morphological operators	Mean	Square and rectangle	Backpropagation neural network	[10]
Direction masks	Standard deviation	Square	Cosine similarity	[33,50]
Gabor filter	Mean and standard deviation	Circular	Cosine similarity	[64]
Directional line detector, Gabor, Haar wavelet	Mean energy, number of line pixel	Rectangle, segments in elliptical half-ring	L_1 norm	[29]
Nil	Zernike moments	Global statistics	Euclidean, L_1 norm	[11]
Wavelet	Center of gravity, density, spatial dispersivity and energy	Global statistics	Sum of individual percentage error	[14]
M-band wavelet	L_1-norm energy, Variance	Global statistics	Euclidean distance	[46]
Nil	Zernike moments	Global statistics	Modular neural network	[49]
Otsu binarization	Hu invariant moments	Global statistics	Euclidean distance	[54]

Hennings-Yeamans et al. employ Log-Gabor filters to assign line-content scores to different regions of palmprints [43,97]. A specific number of regions with top line-content scores are selected to train correlation filters. They use optimal tradeoff synthetic discriminant function (OTSDF) filter as a classifier. Correlation filter is a type of classifiers, extensively studied by Vijaya Kumar and his coworkers [106]. To optimize verification performance, they make use of several user-specific techniques (e.g. user-specific segmentation and user-specific threshold).

Koichi et al. also propose a correlation approach [96]. The amplitude spectrum of two segmented images is used to estimate their rotational and scale differences. One of the images is rotated and scaled and then their amplitude information in the frequency domain is removed. Finally, band-limited phase-only correlation (BLPOC) is used to compute the similarity of two images. BLPOC only considers low to middle frequency information.

Zhang et al. used complex wavelets to decompose palmprint images and propose a modified complex-wavelet structural similarity (CW-SSIM) index for measuring the local similarity of two images [99]. The overall similarity of two palmprints is estimated as the average of all local modified CW-SSIM. CW-SSIM is originally proposed for evaluating image quality [100].

Zhou et al. [92] employ wavelet to decompose palmprints and use support vector machine (SVM) as a classifier. The input of the SVM is low subband images. This approach may overlook some important information in the middle frequency spectrum.

4. Fusion

Fusion is a promising approach that may increase the accuracy of systems [77]. Many biometric traits including fingerprint [82], palm vein [84], finger surface [19,39,80], face [20,62,66,81], iris [88], and hand shape [17,39,50,61,76] have been combined with palmprints at score level or at representation level. Combining other hand features such as hand geometry and finger surface with palmprints allows these features and palmprints to be extracted from a single hand image. Only one sensor is needed. Researchers have examined various fusion rules including sum, maximum, average, minimum, SVM and neural networks. Researchers also fuse features including appearance-based, line and texture features from palmprints [21,29]. Kumar et al. even fuse user identities [62]. Table 3 summarizes the existing fusion approaches. Although fusion increases accuracy, it generally increases computation costs and template sizes and reduces user acceptance.

5. Identification in large databases

5.1. Classification and hierarchical approaches

The problem of real-time identification in large databases has been addressed in three ways: through hierarchies, classification and coding. Hierarchical approaches employ simple but computationally effective features to retrieve a sub-set of templates in a given database for further comparison [14–16]. These approaches increase matching speed at the cost of accuracy. Classifiers can remove target palmprints by using simple features.

Classification approaches assign a class to each palmprint in a database. Wu et al. define six classes based on the number of principal lines and their intersections [22] (Fig. 9). However, the six classes are highly unbalanced, e.g. about 80% of palmprints in category 5 (Fig. 9(e)) and the algorithm has high bin errors of 4%. So these classes are not enough for identification. Li et al. proposed dealing with the unbalanced class [94] problem by further dividing the unbalanced class.

Table 3
Summary of palmprint fusion.

Biometric traits and features	Level of fusion	Ref.
Hand geometry and palmprint	Feature	[9]
Hand geometry and palmprint	Score	[17]
Finger+palmprint	Score	[19]
Face+palmprint	Score	[20]
Gabor+line features+PCA features from palmprints	Score	[21]
Gabor+line+Haar wavelet features from palmprints	Score/decision	[29]
Hand geometry+palmprint+knuckleprint	Feature	[39]
Hand geometry+palmprint	Feature/score	[50]
Face+palmprint+claimed identity	Score	[62]
Face+palmprint	Feature	[66]
Hand geometry+palmprint	Feature/score	[76]
Hand geometry+palmprint+finger surface	Score	[80]
Palmprint+face	Feature	[81]
Fingerprint+hand geometry+palmprint	Score	[23,35,82]
Palmprint+palm vein	Score	[84]
Palmprint+iris	Score	[88]

5.2. Coding approaches

Coding approaches [1,3,4,7,56] use one matching function to search entire databases. This avoids introducing errors from the classification or hierarchical systems but it is difficult to identify effective features for the matching function. Daugman, the inventor of IrisCode, has demonstrated that the bitwise hamming distance allows real-time brute-force identification in large databases [25]. Several coding algorithms similar to IrisCode have been proposed for palmprint identification. PalmCode uses a single Gabor filter to extract the local phase information of palmprint [1,7]. The phase is quantized and is represented in bits and the bitwise hamming distance is used to compare two PalmCodes. The computational architecture is the same as IrisCode. PalmCode always generates highly correlated features from different palms. To remove this correlation, in the first version of Fusion Code [75], we use four directional Gabor filters to generate four PalmCodes. These PalmCodes are combined. For each sample point, only phase information generated by the Gabor filter having maximum magnitude is quantized. Hamming distance is still used to compare two Fusion Codes. In the second version of Fusion Code, the authors carefully examine

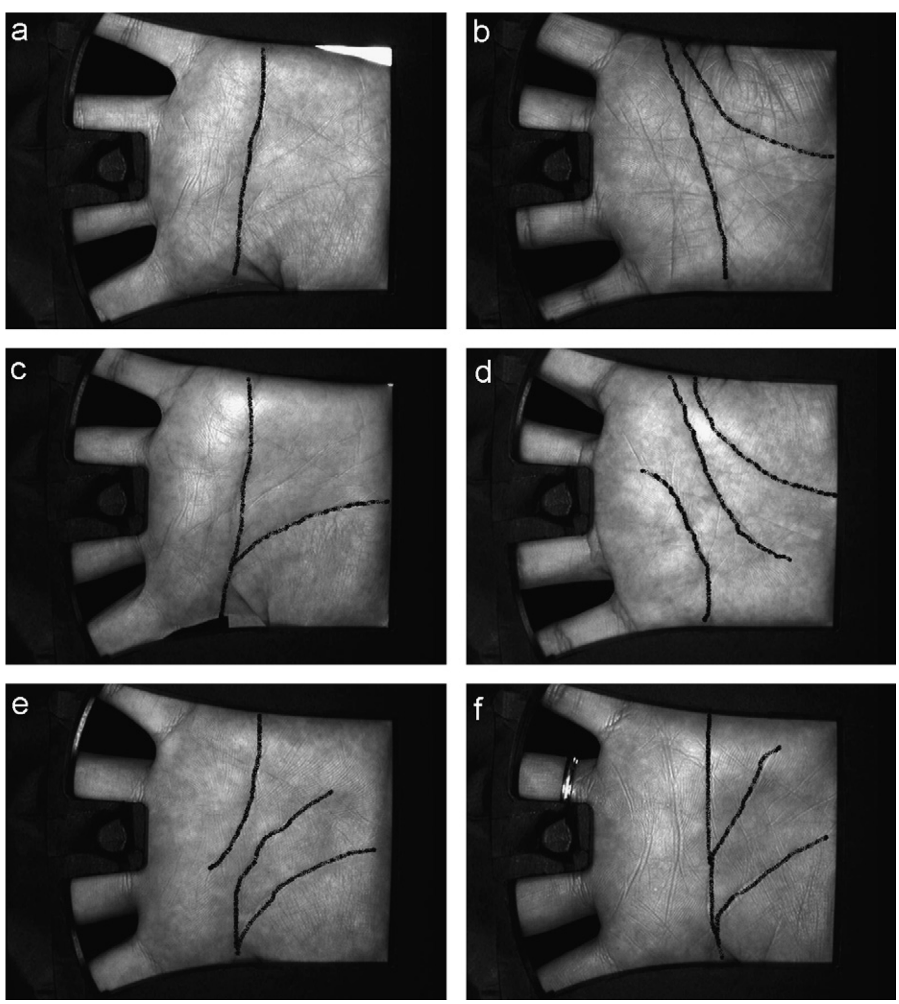

Fig. 9. The six classes of palmprints defined by Wu et al. [22].

the number of Gabor filters and their parameters and find out that the optimal number of Gabor filters is two. They replace the static threshold with a dynamical threshold. The second version of Fusion Code is much more effective than the first.

Both PalmCode and Fusion Code (first and second versions) employ quantized phases as features and the hamming distance as a matcher. Competitive Code [3] uses the orientation field of a palmprint, encoding it for high-speed matching using a novel coding scheme and bitwise angular distance. Like PalmCode and Fusion Code, Competitive Code uses translated matching to improve alignment in preprocessing. A second version of Competitive Code [5], generated 25 translated templates from an input palmprint to match the templates in a database, producing more effective matching codes than the first version. Other researchers have studied this same feature [56,74,85].

Sun et al. used differences between Gaussians to extract orientation fields and bitwise hamming distances for use in matching [56]. Wu et al. modified Fusion Code to extract the orientation field. This algorithm uses the hamming distance but it is not bitwise [57,74] so direct implementation of this algorithm does not support high-speed matching. However, it is possible to replace the non-bitwise hamming distance with the bitwise hamming distance if a suitable coding scheme is provided.

Jia et al. also use the term *code* to describe their method. They modify a finite Radon transform and employ a winner-take-all rule, which is used in Competitive Code, to estimate the orientation field of palmprints. They design a matching scheme called pixel-to-area comparison to improve robustness. Because of the pixel-to-area matching scheme, the matching speed of this algorithm is slower than that of other coding algorithms, which uses bitwise hamming distance and bitwise angular distance.

IrisCode is the foundation of new coding algorithms for palmprints. IrisCode is a clustering algorithm with four prototypes; the locus of a Gabor function is a two-dimensional ellipse with respect to a phase parameter and the bitwise hamming distance can be regarded as a bitwise angular distance [38,79].

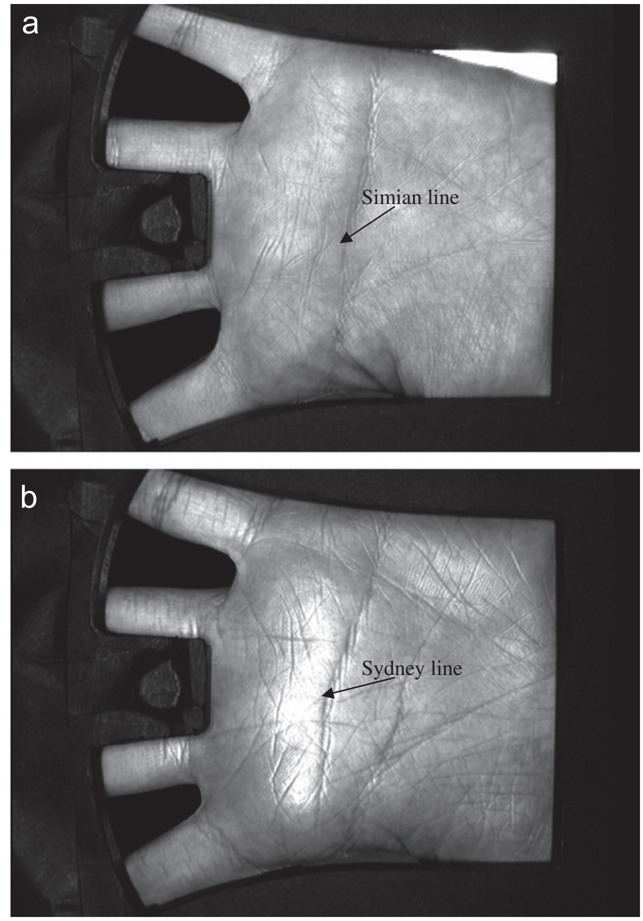

Fig. 10. Abnormal palmprints.

6. Security and privacy

Biometric systems are vulnerable to many attacks including replay, database and brute-force attacks [26]. Compared with verification, fusion and identification, there has been little research on palmprint security. We have analyzed the probability of successfully using brute-force attack to break in a palmprint identification system [5] and proposed cancelable palmprints for template re-issuance to defend replay attacks and database attacks [86]. Connie et al. combined pseudo-random keys and palmprint features to generate cancelable palmprint representations [27]. They claim that their method can achieve zero equal error rates. However, they assume [6] that the pseudo-random keys are never lost and shared and based on this assumption report zero equal error rates for different biometric traits [28]. Sun et al. apply watermarking techniques to hide finger features in palmprint images for secure identification [40]. Wu et al. use palmprint for cryptosystem [87]. Although some security issues have been addressed, it is still not enough. For example, liveness detection has not been well studied. A fake palmprint can be found in [79]. Potential solutions of liveness detection include infrared and multiple spectrum approaches [82,107].

Biometric traits contain information not only for personal identification but also for other applications. For example, deoxyribonucleic acid (DNA) and retina can be used to diagnose diseases. Palmprints can also indicate genetic disorders. Most previous medical research related to the palm has concentrated on abnormal flexion creases, the Simian line and the Sydney line (Fig. 10) [68]. About 3% of normal population has abnormal flexion creases. Medical researchers also discover the association between density of secondary creases and schizophrenia [36]. To protect private information in palmprints, databases store encrypted templates because the line features can be reconstructed from raw templates. Both traditional encryption techniques and cancelable biometrics can be used for encryption. Cancelable biometrics match in the transform domain while traditional encryption techniques require decryption before matching. In other words, decryption is not necessary for cancelable biometrics. When matching speed is an issue, e.g. identification in a large database, cancelable biometrics can hide private information.

7. Discussion and conclusion

Before the end of this paper, we would like to re-mention some papers that are very worthy to read carefully. Our first suggestion is Han's work [9], which is a very complete work. We especially appreciate his palmprint scanner described in this work that can collect images of whole hands and use pegs for hand placement. For verification, we recommend Hennings-Yeomans et al.'s correlation filter approach [97]. They employ many user-specific techniques to optimize accuracy. For real-time large database identification, Kong's Ph.D. dissertation is our suggestion because it contains PalmCode, Fusion Code and Competitive Code and the theory of coding methods. In addition to Kong's work, we also recommend to read the original IrisCode [25] paper, which is the foundation of all coding methods. For fusion, we do not emphasize on any paper in our list because it is well-known that fusion can improve accuracy. Biometric fusion is in fact an application of information fusion and combined classifiers. Many excellent papers have been published in these two fields. For security, we also do not emphasize on any paper because the literature of palmprint security is very small.

In face recognition literature, many researchers design algorithms based on prior knowledge of the face. To optimize the recognition performance in terms of speed and accuracy, we expect that more algorithms are designed based on the prior knowledge of palmprints. Different template formats may require different measures for template protection [86]. More research should be put into security and privacy issues [65,108]. For biometric fusion, the authors recommend combining IrisCode—the commercial iris recognition algorithm and Competitive Code or other coding methods for high-speed large-scale personal identification because these algorithms share a number of important properties (e.g. high speed matching). Even though IrisCode does not accumulate false acceptance rates when the number templates in database increases, its false reject rate still increases. Some issues in using palmprints for personal identification have not been well addressed. For instance, we know that ridges in palmprints are stable for a person's whole life but the stability of principal lines and wrinkles has not been systemically investigated.

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About the Author—ADAMS KONG finished his Ph.D. thesis, "Palmprint identification based on generalization of IrisCode" in the University of Waterloo, 2007. He developed several coding methods including PalmCode, Fusion Code and Competitive Code for high-speed palmprint identification. In addition to identification, he also completed a study about twin's palmprint and proposed security measures for palmprint systems. Although palmprint recognition is his major research area, the best of his work may be the analysis and generalization of IrisCode. Except his professional research, recently, he puts a great focus on global warming. He expresses the messages to his students. More information about Adams Kong can be found at http://www.ntu.edu.sg/home/adamskong/.

About the Author—DAVID ZHANG graduated in Computer Science from Peking University in 1974. In 1983 he received his M.Sc. in Computer Science and Engineering from the Harbin Institute of Technology (HIT) and then in 1985 his Ph.D. from the same institution. From 1986 to 1988 he was first a Postdoctoral Fellow at Tsinghua University and then an Associate Professor at the Academia Sinica, Beijing. In 1994 he received his second Ph.D. in Electrical and Computer Engineering from the University of Waterloo, Ontario, Canada. Currently, he is a Chair Professor, the Hong Kong Polytechnic University where he is the Founding Director of the Biometrics Technology Centre (UGC/CRC) supported by the Hong Kong SAR Government. He also serves as Adjunct Professor in Tsinghua University, Shanghai Jiao Tong University, Harbin Institute of Technology, Beihang University and the University of Waterloo. Professor Zhang's research interests include automated biometrics-based authentication, pattern recognition, and biometric technology and systems. He is the Founder and Editor-in-Chief, International Journal of Image and Graphics (IJIG) (www.worldscinet.com/ijig/ijig.shtml); Book Editor, Kluwer International Series on Biometrics (KISB) (www.wkap.nl/prod/s/KISB); Chairman, Hong Kong Biometric Authentication Society and Program Chair, the First International Conference on Biometrics Authentication (ICBA), Associate Editor of more than ten international journals including IEEE Trans on SMC-A/SMC-C, Pattern Recognition, and is the author of more than 140 journal papers, twenty book chapters and eleven books. As a principal investigator, Professor Zhang's has since 1980 brought to fruition many biometrics projects and won numerous prizes. In 1984 his Fingerprint Recognition System won the National Scientific Council of China's third prize and in 1986 his Real-Time Remote Sensing System took the Council's first prize. In 2002 his Palmprint Identification System won a Silver Medal at the Seoul International Invention Fair, following that in 2003 by taking a Special Gold Award, a Gold Medal, and a Hong Kong Industry Award. Professor Zhang holds a number of patents in both the USA and China and is a Croucher Senior Research Fellow and Distinguished Speaker of IEEE Computer Society.

About the Author—MOHAMED S. KAMEL received the B.Sc. (Hons) EE (Alexandria University), M.A.Sc. (McMaster University), Ph.D. (University of Toronto) He is at present Professor and Director of the Pattern Analysis and Machine Intelligence Laboratory at the Department of Electrical and Compute Engineering, University of Waterloo, Canada. Professor Kamel holds Canada Research Chair in Cooperative Intelligent Systems. Dr. Kamel's research interests are in Machine Intelligence, Image Analysis and Pattern Recognition. He has authored and co-authored over 300 papers in journals, and conference proceedings, 2 patents and numerous technical and industrial project reports. Under his supervision, 63 Ph.D. and M.A.Sc. students have completed their degrees. He is the Editor-in-Chief of the International Journal of Robotics and Automation, Associate Editor of the IEEE SMC, Part A, the Intelligent Automation and Soft Computing, Pattern Recognition Letters, and member of the editorial board of the International Journal of Image and Graphics. Dr. Kamel is member of ACM, AAAI, APEO and Fellow of the IEEE. He served as consultant for General Motors, NCR, IBM, Northern Telecom and Spar Aerospace. He is member of the board of directors and co-founder of Virtek Vision International in Waterloo.