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Survey of Palmprint Recognition

Priyanka Somvanshi, Milind Rane

Abstract— A biometric system is essentially a pattern recognition system which makes a personal identification by determining the authenticity of a specific physiological or behavioral characteristic possessed by the user. Biometric has gained much attention in the security world recently. Many types of personal identification systems have been developed and palmprint verification is one of the emerging technologies because of its stable, unique characteristics, low-price capture device, fast execution speed also it provides a large area for feature extraction. Palmprint recognizes a person based on the principal lines, wrinkles and ridges on the surface of the palm. The recognition process consists of image acquisition, preprocessing, feature extraction, matching and result. The different techniques are used for the preprocessing, feature extraction, classifiers. The methods discussed are for the online palmprint recognition.

Index Terms— Biometrics, preprocessing, feature vector, matching, classifiers, recognition

1 Introduction

PALMPRINT recognition uses the person's palm as a biometric for identifying or verifying who the person is. Palmprint patterns are a very reliable biometric and require minimum cooperation from the user for extraction. Palmprint is distinctive, easily captured by low resolution devices as well as contains additional features such as principal lines, wrinkles and ridges. Therefore it is suitable for everyone and it does not require any personal information of the user. Palmprint images are captured by acquisition module and are fed into recognition module for authentication. Basically palmprint has three modes: Enrollment, Identification and Verification. In personal authentication, palmprint employs either high resolution or low resolution images. The high resolution images refer to 500 dpi or more and suitable for forensic applications such as criminal detection while low resolution images refer to 100 dpi or less and suitable for civil, commercial applications such as access control. Palmprint consists of principal lines, wrinkles and ridges. The principal lines are the major lines existing in most of people palmprint. The three main principal lines are heartline, headline and lifeline. Wrinkles and ridges are the coarse and fine lines of the palmprint respectively. The high resolution images can generally extract all the features while in low resolution only principal lines, wrinkles can be extracted. For real time applications low resolution images are used as they have less storage memory and fast matching speed. Palmprint recognition consists of image acquisition in which image is capture with the help of device. Preprocessing sets up coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction obtains effective features. The matcher compares the extracted features with the features stored in the database.

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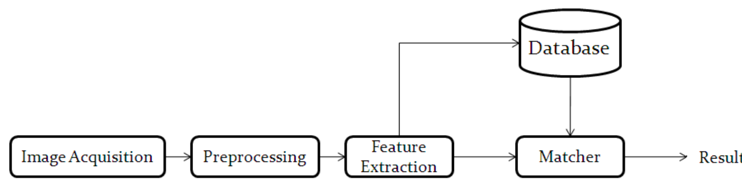
2 Palmprint Image Recognition System



System block diagram

3 Palmprint image acquisition and preprocessing

Palmprint image acquisition has two methods. The offline and online methods are used. In offline the palm is painted with ink and put it on paper then it is scanned. This collection method is very slow, it is not suitable for real time applications. Hence online method is used. In online method CCD-based palmprint scanners are used. These digital scanners [1,2] capture high quality palmprint images and align palms accurately because the scanners have pegs for guiding the placement of hands. This acquired image is further sent for the preprocessing. The preprocessing is used to segment the centre for feature extraction and set up a coordinate system. Preprocessing [1] consists of five steps, 1) binarize the images, 2) boundary extraction, 3) detecting the key points, 4) establish a coordination system and 5) extracting the central part. The image is binarized by Otsu's [3] thresholding method. The algorithms used for the binarizing and boundary extraction are same but detecting key points [3,15] have tangent based [1], bisector based [16] approaches. Zhong et al. [30] proposed the palmprint image adaptive threshold algorithm, boundary tracking and automatic positioning palm ROI by Euclidean distance, which guarantee the accuracy and efficiency of the identification systems. This approach has three advantages: (1) The algorithm is not complicated, (2) Accurate positioning which can reduce the impact of translation and rotation, (3) high noise endurance, good robustness. After establishing co-

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ordinate system the central part is extracted. The central part extracted can be square shaped [3] or circular shaped [17].The square region is easier for handling translation variation, while the circular region is easier for handling rotation variation. The central part extracted can be square shaped [3] or circular shaped [17]. The square region is easier for handling translation variation, while the circular region is easier for handling rotation variation.

4 Feature Extraction

Once the central part is segmented, features can be extracted for matching. The features defined possess the stable and unique properties of low intra-class difference and high inter-class difference. These features are used to create a master template which is stored in the system database. While in Feature matching a matching score is obtained by matching the identification template against the master templates. If the score is less than a given threshold, the user is authenticated. Features from Palmprints are shown in Fig. 1. Many features of a palmprint can be used to uniquely identify a person. In feature extraction low-resolution palmprint recognition approaches can be broadly classified into three categories: holistic-based, feature- based, and hybrid methods. The holistic-based palmprint recognition approaches use the original palmprint image as a whole to extract holistic features. It can be further divided into subspace-based [6], invariant moment-based [7], and transform-based methods [8]. In feature-based approaches, the local features of palmprint are extracted for efficient palmprint recognition. The palmlines and texture are two classes of stable and distinctive local features. The hybrid approaches use both holistic and local features to improve the recognition accuracy and matching speed.

Kong et al. [3] uses the 2-D Gabor filter to obtain the textural information and two palmprint images are compared in terms of their hamming distance. In this method the phase information in palmprint images is stored in the feature vector. However this filter presents a limitation in bandwidth where only filters with the bandwidth of one octave can be designed. Furthermore, large bandwidth Gabor filter introduces a significant dc component. So Field et al. [26] proposed Log-Gabor filters to overcome the bandwidth limitation in traditional Gabor filters. These Log-Gabor filters always have null dc component and desirable high-pass characteristics, i.e. fine details to be captured in high frequency areas. In paper [26] the implementation of Log Gabor function for palm recognition is done, further its efficiency is compared with other existing technique ICA. After testing, result gives the better performance for Log Gabor technique. Gabor filters can provide robust features against varying brightness and contrast of images. However, the procedure for feature coding and matching by pixels requires too much time and memory. Moreover to extract more local features from the original images, a series of Gabor filters with various scales and orientations (i.e Gabor filter bank) are needed. Eventually this will enlarge the feature dimension by time and make feature matching beyond implementation. So Zhiqiang et al. [27] proposes a novel Gabor feature-based two-directional two-dimensional linear discriminant analysis GB(2D)2LDA for palmprint recognition. In GB(2D)2LDA, Gabor feature vector is derived from a Gabor filter bank, then (2D)2LDA uses the augmented Gabor feature vector as an input. Meanwhile, GB(2D)2LDA can reduce the augmented Gabor feature vector in horizontal and vertical directions sequentially, and hence fewer coefficients are required for image representation and recognition. Hence the GB(2D)2LDA is effective in both recognition accuracy and speed. As Gabor filter based texture information extraction method is both time and memory intensive to convolve palm images with a bank of filters to extract features. In the paper by Meiru et al. [31] a novel palmprint texture representation is proposed, discriminative local binary patterns statistic (DLBPS) which is extracted for palmprint recognition. In this approach, a palmprint is firstly divided into non-overlapping and equal-sized regions, which are then labeled into Local Binary Patterns (LBP) independently. By calculating these patterns distribution, the statistic features of the palmprint texture are attained. Subsequently, the Discriminative Common Vectors (DCV) algorithm [31] is applied for dimensionality reduction of the feature space and solution of the optional discriminative common vectors. Finally, Euclidean distance and the nearest neighbor classifier are used for palmprint classification.J. You et al. [24] introduced a texture-based dynamic selection scheme facilitating the fast search for the best matching of the sample in the database in a hierarchical fashion. The global texture energy, which is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination, is used to guide the dynamic selection of a small set of similar candidates from the database at coarse level for further processing. An interesting point based image matching is performed on the selected similar patterns at fine level for the final confirmation. Furthermore only the palmlines as feature are extracted using the edge detector. Wong et al. [25] applied the different Sobel operators to the resized palmprint image. The Sobel image is thresholded and represented using feature vector. The feature vector is in logical format that has the value of zero or one. All of the feature vectors are compared using Hamming distance similarity. An accuracy of 94.84 percent can be achieved using the proposed method.

Another method for feature extraction is subspace-based approaches like Principal Component Analysis (PCA) [6], Fisher Discriminate Analysis (FDA) [7], Independent Component Analysis (ICA) [11] are used to reduce the feature size. Lu et al. [1] are among the first to propose the use of PCA in the palmprint recognition. It finds a set of orthogonal basis vectors. It describes the major variations among the training images. The bases have the same dimension as the original images and are like palmprint in appearance, they are also called eigenpalms. PCA can only separate pair-wise linear dependencies between pixels. It reduces the dimensionality. The basic idea of ICA [2] is to decompose an observed signal (mixed signal) into a set of linearly independent signals. In [3] the palmprint images are considered as the mixture of an unknown set of statistically independent source images by an unknown mixing matrix. A separating matrix is learnt by ICA to recover a set of statistically independent basis images. The bases generated are spatially localized in various portions in the palmprint image. ICA offers a more generalized method which can separate higher-order dependency. FDA [3] is another subspace projection technique which computes a subspace that best discriminates among classes. It deals directly with class separation. The bases generated using FDA are also known as fisherpalms. FDA tends to take into account the within and between-class scatter for classification. Its intention is to maximize the between-class scatter as to minimize the within-class scatter. FDA provides more class separability by building a decision region between the classes. It transforms the samples into the 'best separable space' focusing on the most discriminant feature extraction. Yuping Wang et al.[33] proposed Kernel fisher discriminant analysis (KFDA) which is the current research focus for non-linear machine learning methods. Kernel fisher discriminant analysis is essentially a complex learning system which is the combination of a kernel method and fisher discriminant analysis method. It considers more high-dimensional statistics, so it can be more effective to distinguish different types of palmprint algebraic features. Another approach of projection method is Locality preserving projections (LPP). The objective of LPP is to preserve the local structure of the image space by explicitly considering the manifold structure, which is in fact to solve a generalized eigenvalue problem. D. Hu et al. [23] proposed the two-dimensional locality preserving projections (2DLPP), which directly extracts the proper features from image matrices based on locality preserving criterion.

Coding-based method is one class of the local feature-based approaches [10,12,13]. It encodes the responses of a bank of filters into bitwise feature code. With the virtue of bitwise representation, coding based method usually has low memory requirement and fast matching speed, and thus has been very successful in palmprint representation and matching. Recent advances in coding-based method indicate that the orientation information of palm lines is one of the most promising features for personal identification. The methods based on orientation information have achieved state-of-the-art verification accuracy. Among various schemes, the orientation based coding methods have merits of high accuracy, robustness to illumination variation and fast implementation. For accurate orientation feature extraction, Zuo et al. [7] propose a high order steerable filter based approach [7], which is comparable to filterbank- based approach in term of accuracy and is more computationally efficient and the proposed generalized orientation distance measure satisfy the matching speed for practical applications obtaining state-of-the-art verification accuracy. The orientation of palm lines is stable and can provide enough discriminatory information for personal identification. One of them is competitive code (Comp-Code) introduces by Kong et al.[40], then palmprint orientation code (POC) introduced by Wu et al. [41] and the robust line orientation code (RLOC) introduced by Jia et al. [10]. These algorithms use different filters or masks, such as Gabor filter (CompCode), self designed mask (POC), and modified finite Radon transform (RLOC) to estimate the orientation feature of each local region. A common rule, the ''competition" rule, is shared by these algorithms: several filters or masks with different orientations are convolved with the image and then the ''dominant" orientation is determined with some criterion. By simply coding the orientation map of the palmprint high accuracy palmprint identification could be implemented with high speed matching. The original competitive coding scheme only simply selects as orientations of Gabor filters, and thus neglects the characteristics of the orientation distribution of palmlines since it is not uniformly distributed. To overcome this problem Yue et al. [8] proposed the modified (fuzzy C-means) FCM algorithm. Hence it is more suitable to find the orientations representing palmprint best. Later Wangmang et al. [29] represents a compact multiscale palm line orientation features, and proposes a novel method called the sparse multiscale competitive code (SMCC). Compared with the existing mono-scale and multiscale palmprint recognition methods, the SMCC achieves better verification performance as it is insensitive to illumination and scaling factors, and thus it is effective as a potential texture descriptor. Further an improved version of Competitive Code i.e. a novel scheme robust line orientation code (RLOC) has been proposed by Wei et al. [10]. RLOC uses the modified finite Radon transform (MFRAT) to extract the orientation feature of palmprint more accurately and solve sub-sampling problem better. The advantage of this method is that the use of an enlarged training set can overcome large rotations problem well. Also the designed pixel-to-area comparison has better fault tolerant ability. It has three times faster speed than the Competitive Code. Guo et al. [12] proposed a novel feature extraction algorithm, namely binary orientation co-occurrence vector (BOCV) to represent multiple orientations for a local region. The BOCV can better describe the local orientation features and it is more robust to image rotation. The experimental results on the public palmprint database show that the proposed BOCV outperforms the CompCode, POC and RLOC by reducing the equal error rate (EER) significantly. In the PalmCode introduced by kumar et al. [39] uses a single Gabor filter to extract the local phase information of palmprint. The phase is quantized and is represented in bits and the bitwise hamming distance is used to compare two PalmCodes. PalmCode always generates highly correlated features from different palms. To remove this correlation, in the first version of Fusion Code four directional Gabor filters are used to generate four PalmCodes. Multiple elliptical Gabor filters with different orientations are employed to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the Fusion Code introduced by Kong et al. [27]. The similarity of two Fusion Codes is measured by their normalized hamming distance. As palmprint image contains various features with multiple orientations, so only a single orientation in the palmprint cannot distinguish a subject well. Therefore Zhao et al. [32] introduced the 2D Orthogonal Gabor filters with different orientations are employed to extract texture information and a phase-coding scheme is used to represent the palmprint. At the matching stage, Hamming distance is used as a similarity metric.

In transform-based feature extraction methods Discrete Cosine Transform (DCT) [14], Discrete Fourier Transform [16], Wavelet Transform [4], contourlet transform [38] are used. In DFT by Li et al. [16] the palmprint image is first converted into the frequency domain image. These different features are used to lead a layered fashion searching for the best matching with the templates in the database. But in FT only the global variations are captured. In the proposed DCT-based palm-print recognition scheme by Jing et al. [14], instead of operating on the entire palmprint image at a time the dominant spectral features are extracted separately from each of the narrow-width band obtained by image segmentation. It has been found that the proposed feature extraction scheme offers two-fold advantages. First, it can precisely capture local variations that exist in the palm-print images, which plays an important role in discriminating different persons. Second, it utilizes a very low dimensional feature space for the recognition task, which ensures lower computational burden. In DCT, the palmprint image is analyzed in single resolution. Since the palm lines, such as principal lines, wrinkles and ridges can only be acquire in different resolution, multi resolution analysis using Wavelet Transform is proposed by Lu et al. [4] as it has better space-frequency localization. Multi-resolution analysis of the images is performed by reiterating the wavelet decomposition to an arbitrary number of times on the low frequency part. At the first level, the original image is decomposed in four sub-bands leading to the scaling component containing global low-pass information and three wavelet components corresponding to the horizontal, vertical and diagonal details. Multi resolution wavelet transform can extract different types of line in different resolution level. The level one decomposition allows the extraction of ridges information. When the decomposition level increases, larger palm lines such as wrinkles and principal lines are extracted. As there are limitations of commonly used separable extensions of one- dimensional transforms, such as the Fourier and wavelet transforms, in capturing the geometry of image edges are well known Ardabili et al. [38] introduced contourlet transform. The contourlet transform is a new extension to the wavelet transform in two dimensions using nonseparable and directional filter banks. The contourlet transform uses contour segments and fine details in images to realize the local, multiresolutional and directional image expansion. Contourlet is implemented by the Pyramidal Directional Filter Banks (PDFB) that is a cascade of a Laplacian Pyramid (LP) and Directional Filter Banks (DFB). In contourlet transform, the Laplacian pyramid does the decomposition of images into sub-bands and then the directional filter banks analyze each detail image. The contourlet transform has the multi-scale and time-frequency localization properties of wavelets, but also offers a high degree of directionality and anisotropy. These properties are very important in palmprint verification.

5 Recognition/Classification Methods Used

A In palmprint verification mode the input palmprint image is matched with the palmprint image in the available database. For matching palmprint image many distances are defined. In the [3] Palmprint matching is based on a normalized hamming distance. It is bitwise operation and uses the XOR operator. The distance is in between range 0 to 1. The hamming distance for perfect matching is zero. To implement a real-time palmprint identification system requires a simple and powerful palmprint matching algorithm. So for the Competitive Code [41] an angular distance is designed for comparing two codes. The distance is between 0 and 1. For perfect matching, the angular distance is zero. In the current systems firstly, the user's palmprint is captured by the system. Then, it is compared to every single image in the database, and a result is produced. This method is very time consuming and computational complexity is also too high to be practical. Palmprint classification provides an important indexing mechanism in a palmprint database. An accurate and consistent classification can greatly reduce palmprint matching time for a large database. Wu et al. [40] proposed the classification of palmprints using principle lines. The algorithm has the ability to classify low-resolution palmprint into six categories according to the number of principal lines and the number of their intersections. These are mainly palms with one principal line, two principal lines without intersection, two principal lines with intersection, three principal lines without intersection, three principal lines of which two intersects and three principal lines of which all lines intersects each other. The proportions of these six categories (1–6) from a 13,800 samples database [40] are 0.36%, 1.23%, 2.83%, 11.81%, 78.12% and 5.65%, respectively. The proposed algorithm is to classify palmprint with an accuracy of 96.03%. If an input palmprint image falls into Category 5, the matching process may still have to search through 78.12% of the original database samples before finding a match. So category 5 is subdivided into 5 subcategories A, B, C, D, E. The result is well-distributed. Among all the samples belong to category 5, 17.6% of them belong to category A, 22.3% of them to category B, 18.3% of them to category C, 23.1% of them to category D, and 18.7% of them to category E. This affirms the effectiveness of the algorithm. In [35] Kumar et al. uses the nearest neighbor (NN) classifier for the classification of extracted feature vectors. The NN classifier is a nonparametric classifier which computes the minimum distance between the feature vector of unknown sample g and that of for gm in the mth class. The class label corresponding to closet training sample is assigned to feature vector g. Three distance measures i.e. L1, L2, Lcos are used in [35] to evaluate the performance of feature sets of gabor, line, PCA. Each of the three feature sets obtained from the three different palmprint representations were experimented with each of the above

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three distance measures. The distance measure that achieved best performance was finally selected for the classification of feature sets from the corresponding palmprint representation. K-nearest neighbor is a supervised learning algorithm. The new instance of palmprint is classified on the basis of the majority of K-nearest neighbor category. To find out closest neighbor, calculate angular or hamming distance [34] to each training sample and then sort it in ascending order and then find K nearest training sample. The purpose of this algorithm is to classify a query palmprint image based on attributes and training samples. Given a palmprint image, we find K number of training palmprints closest to the query palm. KNN classifier can be breaking any tie at random. KNN classifier is robust to noisy training data and effective also if data is large. Verification of a query palmprint image is determined by the class of its K-nearest neighbors if class of a query palmprint image is same as output of the K-nearest neighbor classifier, then palmprint is matched with training samples otherwise not matched. In [36] results using the combination HMAX model and support vector machine (SVM) classifier obtains higher recognition rate than those obtained with HMAX model and K-nearest neighbors (KNN) classifier in identity verification system based on palmprint, and also demonstrated that the HMAX model, compared with PCA method, not only obtains higher recognition rate, but also this method is scale and rotate invariant, whereas PCA method provide high recognition rate only in closely controlled conditions. SVM operates on the principle of Structural Risk Minimization (SRM). It constructs a hyper-plane or a set of hyper-planes on a high dimensional space for the classification of input features. The data to be classified by the SVM may not be linearly separable in the original feature space. In the linearly non-separable case the data is projected onto a higher dimensional feature space using Kernel function. Then SVM generates a hyper-plane in H with the decision boundary. SVMs have two basic advantages: First, the kernel techniques can be used to convert nonlinearly separable densities into a pair of linearly separable ones and second SVMs minimize the maximum expected generalization error, leading to good generalization ability. While in [38] the AdaBoost algorithm is used to classify unknown palmprint images. It is a very promising method for invariant palmprint verification. AdaBoost is a very popular boosting algorithm. It assigns each sample of the given training set a weight. All weights are initially set equal, but in every round the weak learner returns a hypothesis and the weights of all examples classified wrong by that hypothesis are increased. Therefore, the weak learner will focus on the difficult samples in the training set. The final hypothesis is a combination of the hypotheses of all rounds and hypotheses with lower classification error have higher weight. The following table gives the summary of the palmprint recognition system.

TABLE 1

SUMMARY OF PALMPRINT RECOGNITION

Method	Feature	Classifier	Data Set	Accuracy (%)
Gabor	Phase information	Hamming Distance	4647	97.59
Log Gabor	Training vector	Probabilistic neural network	80	92.5
GB(2D)2LDA	Gabor feature vector	Nearest neighbor	7752	99
Hierarchical multiple feature	Texture Energy	HIMS	256	95
Sobel	Line feature	Hamming Distance	100	94.84
DLBP	LBP statistic feature vector	Euclidian distance	1460	98.95
DFT	Statistic feature	Hamming Distance	2500	95.48
DCT	Spectral features	Distance based	7752	99.97
Wavelet Transform	Wavelet energy features	Neural network	1000	98
Contour Transform	Feature vectors	AdaBoost(α-Type)	240	97.3
PCA	Eigen palm	L1	900	92.4
ICA	Texture feature	Lcos	900	95.7
FDA	Fisher palm	L1	900	95.2
Competitive Code	Feature code	Angular distance	7752	98.4
RLOC	Orientation feature	Pixel to area matching	7752	98.37
Palm Code	Feature vectors	Hamming Distance	800	97.50
Fusion Code	Fusion code	Hamming Distance	9599	96.33
BOCV	Binary feature	Hamming Distance	7752	98.3

6 CONCLUSION

Palmprint recognition has considerable potential as a personal identification technique as it shares most of the discriminative features with fingerprints and in addition possesses a much larger skin area and other discriminative features such as principal lines, ridges and wrinkles. An attempt is made to design algorithms to extract maximum features from low resolution with high accuracy. Coding based techniques have proven to be efficient in terms of memory requirement and matching speed. Researchers have also tried to fuse features like appearance-based, line and texture features from palmprints, which has led to an increase in accuracy. Pixel-to-area

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based matching techniques are much more fault tolerant as compared to traditional pixel-to-pixel based matching techniques. The properties like multi-scaling, time-frequency localization, high degree of directionality and anisotropy are very useful in the palmprint verification. Using multi resolution schemes the finer local feature details can be extracted. Nowadays multi-scale, multi-resolution based techniques like wavelets and contourlets are being explored as potential candidates for efficient implementation of palm print recognition.

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REFERENCES

[1] D. Zhang, W.K. Kong, J. You and M. Wong, "On-line palmprint identification", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 25, no. 9, pp. 1041-1050, 2003.
[2] C.C. Han,"A hand-based personal authentication using a coarse-to-fine strategy", Image and Vision Computing, vol. 22, no. 11, pp. 909-918, 2004.
[3] W.K. Kong, D. Zhang and W. Li, 2003, "Palmprint feature extraction using 2-D Gabor filters", Pattern Recognition, vol. 36,pp. 2339-2347, Oct. 2003.
[4] G. Lu, K. Wang and D. Zhang "Wavelet based feature extraction for palmprint identification", in Proceeding of Second International Conference on Image and Graphics, pp. 780-784, 2002
[5] G. Y. Chen, T. D. Bui, A. Krzyak, "Palmprint classification using dual-tree complex wavelets," International Conference on Image Processing, 2006, pp. 2645–2648.
[6] T. Connie, T. Andrew, K. Goh, "An automated palmprint recognition system," Image and Vision Computing, vol. 23, 2005, pp. 501–505.
[7] X. Wu, D. Zhang, K. Wang,"A Fisherpalms based palmprint recognition," Pattern Recognition Letters, vol. 24, 2003, pp. 2829–2838.
[8] F. Yue, W. Zuo, D. Zhang, "Orientation Selection Using Modified FCM for the Competitive Code-based Palmprint Recognition,"Pattern recognition, vol. 42, pp. 2841-2949, 2008
[9] Z. Guo, W. Zuo, L. Zhang, D. Zhang, " A unified distance measurement for orientation coding in palmprint verification", Neurocomputing, vol. 73, 2010 pp. 944-950.
[10] W. Jia, D.S Huang and D. Zhang, "Palmprint verification based on robust line orientation code", Pattern Recognition, vol. 41, no. 5, pp. 1504-1513, 2008
[11] L. Shang, D.S. Huang, J.X. Du and Z.K. Huang, "Palmprint recognition using ICA based on winner-take-all network and radial basis probabilistic neural network", LNCS 3972,pp. 216-221, 2006.
[12] Zhenhua Guo, David Zhang, Lei Zhang, Wangmeng Zuo, "Palmprint verification using binary orientation co-occurrence vector", Pattern Recognition Letters 30 (2009) 1219–1227
[13] A. Kong, D. Zhang, M. Kamel, "Survey of Palmprint Recognition", Pattern Recognition, vol. 42, 2009, pp. 1408 – 1418.
[14] Xiao-Yuan Jing and David Zhang,"A Face and Palmprint Recognition Approach Based on Discriminant DCT Feature extraction", IEEE TRANSACTIONS ON SYSTEMS,MAN,AND CYBERNETICS PART B: CYBERNETICS, VOL. 34, NO. 6, DECEMBER 2004
[15] Deepti Tamrakar, Pritee Khanna, "Analysis of Palmprint Verification using Wavelet Filter and Competitive Code", International Conference on Computational Intelligence and Communication Networks, 2010
[16] W. Li, D. Zhang, Z. Xu, "Palmprint identification by Fourier transform", International Journal of Pattern Recognition and Artificial Intelligence, vol. 16, no. 4, pp. 417-432,2002.
[17] Tian Qichuan, Li Ziliang, Zhu Yanchun, "A Novel Palmprint Segmentation and Recognition Algorithm", International Conference on Intelligent Computation Technology and Automation, 2010.
[18] L. Zhang and D. Zhang, 2004, "Characterization of palmprints by wavelet signatures via directional context modeling", IEEE Trans. on SMC-B, vol. 34, pp. 1335-1347, June 2004.
[19] Zhenhua Guo, D. Zhang, Lei Zhang, Wangmeng Zuo, "Palmprint verification using binary orientation co-occurrence vector", Pattern Recognition Letters 30 (2009) 1219–1227
[20] Feng Yue, WangmengZuo, DavidZhang, KuanquanWang, "Orientation selection using modified FCM for competitive code-based palmprint recognition", Pattern Recognition 42 (2009) 2841 – 2849
[21] G. Lu, D. Zhang, K. Wang, "Palmprint recognition using eigenpalms features", Pattern Recognition Letters 24(9-10),2003, pp. 1473-1477.
[22] Tee Connie, Andrew Teoh, Michael Goh, David Ngo, "Palmprint Recognition with PCA and ICA'' Palmerston North, November 2003
[23] Dewen Hu, Guiyu Feng, Zongtan Zhou, "Two-dimensional locality preserving projections (2DLPP) with its application to palmprint recognition", Pattern Recognition 40 - 339 – 342,2007.
[24] J. You, W. Li, D. Zhang, "Hierarchical palmprint identification via multiple feature extraction", Patt. Recog. 35-847–859,2002.
[25] Wong, K.Y.Edward ,Chekima, Dargham, Sainarayanan, "Palmprint identification using Sobel operator", 10th Intl. Conf. on Control, Automation, Robotics and Vision Hanoi, Vietnam, 978-1-4244-2287 IEEE, 2008
[26] R. Malviya, R. Kumar, A.Dangi, P. Kumawat, "Verification of Palm Print Using Log Gabor Filter and Comparison with ICA", International Journal of Computer Applications in Engineering Sciences, Special vol I, special issue on cns , issn:2231-4946, 2011.
[27] Zhiqiang Zenga, P. Huangb "Palmprint Recognition using Gabor feature-based Two-directional Two-dimensional Linear Discriminant Analysis", International Conference on Electronic & Mechanical Engineering and Information Technology, IEEE, vol. 34, ISBN: 978-1-61284-087-1 pp. 1917 – 1921, Sept 2011

ISSN 2229-5518

[28] A. Kong, D. Zhang, M. Kamel, "Palmprint Identification Using Feature-Level Fusion," Pattern Recognition, vol. 39, pp. 478-487, 2006.
[29] A. Kong and D.Zhang, "The Multiscale Competitive Code via Sparse Representation for Palmprint Verification", vol no.978, pp-4244-6985 IEEE,2010
[30] Zhong Qu, Zheng-yong Wang ,"Research on Preprocessing of Palmprint Image Based on Adaptive Threshold and Euclidian Distance", Sixth International Conference on Natural Computation (ICNC 2010)IEEE, 2010
[31] M.M.Q. Ruan, Y. Shen, "Palmprint recognition based on discriminative local binary patterns statistic feature", International Conference on Signal Acquisition and Processing, IEEE, 2010
[32] Zhao Song, Xu Yan, Liu YuanPeng," Palmprint Verification based on Orthogonal Code", Third International Conference on Information and Computing, 978-0-7695-4047-4 IEEE, 2010
[33] Yuping Wang, Jun Zhang, Mingchuan Meng, "The Study of Identification Algorithm Based on Palmprint Algebraic Features", Print ISBN: 978-1-4244-8162-0, pp-3274 – 3277, IEEE,2011
[34] Y. Song, J. Huang, D. Zhou, H. Zha, C. L. Giles, "IKNN: Informative K-Nearest Neighbor Pattern Classification," Springer-Verlag Berlin Heidelberg, J.N. Kok et al. (Eds.): PKDD, pp. 248–264. 2007,
[35] A. Kumar, D. Zhang, "Personal authentication using multiple palmprint representation", Pattern Recognition 38 (2005) 1695 – 1704, 2005.
[36] S. Motamed, K. Faez, M. Yaqubi, "Palmprint recognition using HMAX model and Support vector Machine classifier ", Pattern Recognition 38-1695 – 1704, 2005.
[37] Hafiz Imtiaz and Shaikh Anowarul Fattah , "A DCT-based Feature Extraction Algorithm for Palm-print Recognition", 978-1-4244-7770 IEEE, 2010
[38] E. Ardabili, K. Maghooli, E. Fatemizadeh, "Contourlet Features Extraction and AdaBoost Classification for Palmprint Verification", Journal of American Science 7(7):353-362(ISSN: 1545-1003),2011
[39] Ajay Kumar, Helen C. Shen, "Palmprint Identification using PalmCodes", Proceedings of the Third International Conference on Image and Graphics INSPEC Accession Number: 8394225 pp 258 – 261, IEEE, 2005
[40] X. Wu, D. Zhang, K. Wang and B. Huang, "Palmprint classification using principle lines", Pattern Recognition, Vol 37, No 10, pp1987-1998, Oct 2004
[41] A. Kong and D.Zhang, "Competitive Coding Scheme for Palmprint Verification", Proceedings of the 17th International Conference on Pattern Recognition, IEEE,2004.