Palm Vein Recognition Using Enhanced Symmetry Local Binary Pattern and SIFT Features

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***Abstract*— Recently, palm vein recognition is new biometric technology with a high degree of privacy and security because this technique uses the blood vessels under the palm skin to establish identification. This paper proposes a novel palm vein feature extraction method for contactless palm vein recognition based on combining enhanced center-symmetric local binary pattern (ECS-LBP) with SIFT, called EL-SIFT. The proposed method includes two steps: (1) applying ECS-LBP to detect stable and clear palm-vein lines; and (2) extracting SIFT feature on palm vein lines image. The experimental results on the public contactless palm vein databases (CASIA Multi-spectral Palm vein Image Database V1.0) show that our proposed method is accurate and robust for palm vein recognition in comparing with other approaches in the literature.**

Keywords*— *Palm vein recognition, local binary pattern (LBP), center-symmetric local binary pattern (CS-LBP,) SIFT, biometrics.

I. Introduction

Nowadays, biometrics is a study of methods for uniquely recognizing individuals based on one or more intrinsic physical or behavioral traits, including the extensively studied fingerprint, facial features, iris, speech, hand geometry, palmprint and palmvein [1] [4] [5] [6]. Among these traits, palm vein is a new biometric feature for personal recognition with a high degree of privacy and security because the palm vein recognition technique uses the blood vessels under the palm skin to establish identification [1]. Furthermore, contactless vein recognition is more hygienic and user-friendly than other methods, which improves users' acceptance. Palm vein imaging requires near-infrared (NIR) light for the complex vascular structures residing inside the palm to become visible. The blood vessels, which absorb the NIR illumination, appear darker than other tissues. Palm vein images are thus grey-level images in which dark grey to black veins appear on the grey background [2]. Generally, palm vein images provide richer texture information, thereby improving the distinguishing ability, which is increasingly attractive to researchers [3]. There are many different methods studied for palm vein processing and feature extraction. The existing algorithms could be divided into three categories: subspace-based, line-based and texture-based methods [2].

Subspace learning based approaches: In subspace learning, the palm-vein images are projected into subspaces to generate subspace coefficient (feature) which are employed during the matching stage for the identification. Subspace was built from training data. Various subspace-based methods have been explored for the palm-vein identification: principal component analysis (PCA) [42] and locality preserving projection (LPP) in [43], (2D)2LDA [44]. Line/curve-matching based approaches apply several filters for extracting curve- or line-like features, such as: Gabor filtering [7] [8], [9], orthogonal Gaussian filters [10], cutoff Gaussian filters [11], matched filters [12], [13], SUSAN edge detector [14], multi-scale Gaussian matched filtering [15], Gaussian filtering and iterative closest point (ICP) matching for alignment of vein structures [13] and complex matched filtering [16]. The extracted line features are further encoded to form a template and employed during the identification. Line-structure pattern-based approach proposed by Ojala et al. for texture classification [17]. Some variants of LBP have been proposed such as center-symmetric local binary pattern (CS-LBP) [18], local ternary pattern (LTP) [19], local derivative pattern (LDP) [20] and completed local binary pattern (CLBP) [21]. The LBP operator has been proposed for face recognition [22, 23], finger vein recognition [24], dorsal hand vein recognition [25, 26], palm-print recognition [27] and palm vein [28]. The LDP operator was proposed for face recognition [29], finger vein recognition [30, 31] and palm vein [28]. Hierarchical multi-scale local binary pattern (HM-LBP) was proposed for palmprint recognition [32]. Mirmohamadsadeghi et al. [33] investigated features for palm vein recognition using LBP, LDP operators and the fusion of the two. It is found that the LDP operator consistently outperforms the LBP operator in palm vein recognition. Luo et al. [34] proposed local line directional patterns (LLDP) which define an LBP-like descriptor that operates in the local line-geometry space, for robust palm-print recognition. In recent years, contactless biometric systems have been developing. The presence of significant scale, rotation, occlusion and translation variations in the contactless images requires the feature extraction algorithms which are tolerant of such changes. Therefore traditional feature extraction methods could not be useful in contactless frameworks. Jiansheng Chen et al. [36] employed the SIFT (Scale Invariant Feature

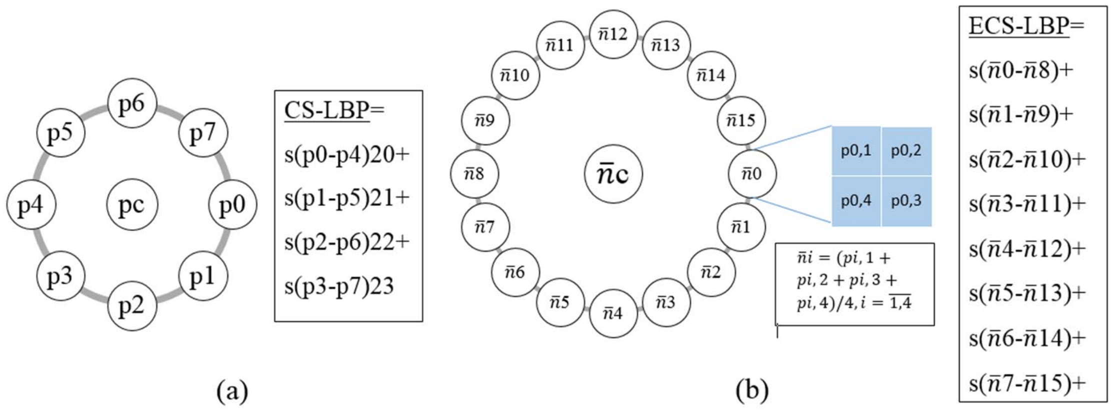

Fig. 2. (a) CS-LBP feature with 8 neighbor points and (b) ECS-LBP feature with 16 neighbor blocks (blocks include 4 points)

Transformation) for palmprint authentication. Point-wise matching is used to match SIFT key points extracted from palmprint images [36]. Aythami Morales et al. [37] used SIFT is proposed to address the large intra-class variations from contactless imaging and examined the performance from possibly the best approach in the palmprint literature using OLOF approach [37]. Xuekui Yan et al. [3] pointed that most of the contactless palm vein images are unclear and have low contrast, if a SIFT algorithm is directly adopted for feature extraction on the center region of a palm vein image, it will be difficult to obtain sufficient features for effective recognition. Therefore, Xuekui Yan et al. performs different Gaussian (DoG) and then conduct the histogram equalization on the DoG images to highlight the vein texture [3]. In order to isolate the texture, CS-LBP is proposed and apply to enhance the SIFT performance for category classification [18]. It should be noticed that the CS-LBP is closely related to the gradient operator because it considers gray-level differences between pairs of opposite pixels in a neighborhood. Moreover, in order to capture large-scale textural structure, Pavel Král et. al [35] proposed Enhanced Local Binary Patterns (ELBP) for face recognition. ELBP computes the feature value from point-sets instead of the isolated points. From these advantages of CS-LBP, ELBP, and SIFT, this paper proposes a novel palm vein feature extraction method for contactless palm vein recognition based on combining Enhanced CS-LBP with SIFT, called ECSL-SIFT. Enhanced CS-LBP, a modified version of CS-LBP, is proposed to highlight the palm-vein texture with the aim that the SIFT algorithm operates well for feature extraction. The experimental results on the public contactless palm vein databases (CASIA Multi-spectral Palm vein Image Database V1.0) show that our proposed method is accurate and robust for palm vein recognition in comparing with other approaches in the literature.

The rest of the paper is organized as follows. Section 2 we introduce proposal methods. The experimental results are presented in section 3. Finally, the paper conclusions are drawn in section 4.

II. PROPOSAL METHOD

The proposed method includes two steps: (1) applying ECS-LBP to detect stable and clear palm-vein lines; and (2) extracting SIFT feature on palm vein lines image (Fig. 1).

Fig. 1. The scheme of the proposal method.

A. ECS-LBP for enhancing palm-vein patterns

Before presenting in detail the ECS-LBP operator, we give a brief review of CS-LBP methods that form the basis for our work.

1) LBP

LBP(Local Binary Pattern) describes the local spatial structure of images, it possesses a strong capability of classification, higher calculation efficiency, gray level invariance, and rotational invariance. The LBP operator is depicted by [21]:

$$LBP_{P,R} = \sum_{p=0}^{P-1} S(g_{p-g_c})2^p, \;\; s(a) = \begin{cases}1, a \geq 0\\ 0, a < 0\end{cases} \quad (1)$$

Where g_c is the gray value of central pixel; g_p represents the gray value of nearby pixels; P controls the sampling density which represents the number of nearby pixels; radius R controls the scale of LBP operator.

2) CS-LBP

CS-LBP compares center-symmetric pairs of pixels (Fig. 2a). The robustness on flat image regions is obtained by thresholding the gray-level differences with a small value T as proposed in [18]:

$$CS-LBP_{R,N,T}(x,y) = \sum_{i=0}^{(N/2)-1} s(p_i - p_{i+(N/2)})2^i,$$
$$s(x) = \begin{cases}1 & x > T\\ 0 & otherwise\end{cases} \quad (2)$$

where p_i and $p_{i+(N/2)}$ correspond to the gray values of center-symmetric pairs of pixels of N equally spaced pixels on a circle of radius R. The CS-LBP is closely related to gradient operator, because like some gradient operators it considers gray-level differences between pairs of opposite pixels in a neighborhood.

3) ECS-LBP

Similar to the enhanced LBP [38], Enhanced CS-LBP (ECS-LBP), modify version of CS-LBP, computes the feature values from blocks (point-sets) instead of the isolated points. The ECS-LBP feature is created in a similar way as the original CS-LBP operator as follows:

$$ECS-LBP_{R,N}(x,y) = \sum_{i=0}^{(N/2)-1} s(\bar{p}_i, \bar{p}_{i+(N/2)})2^i \,,$$

$$s(x,y) = \begin{cases} 1 & x > y \\ 0 & otherwise \end{cases}$$

$$\bar{p}_i = \frac{1}{w}\sum_{j=1}^{w} p_j \,, (3)$$

Where $\bar{p}_i$ is the average gray value of the neighboring pixel intensities of point p_j (Fig. 2b). Similar to CS-LBP,$\bar{p}_i$ and $\bar{p}_{i+(N/2)}$ corresponds to the center-symmetric pairs of pixels of N equally spaced pixels on a circle of radius R. Note that it is possible to consider several point-set topologies of different sizes to capture different texture information. In our method, the square shapes of the sizes 2×2, are used.

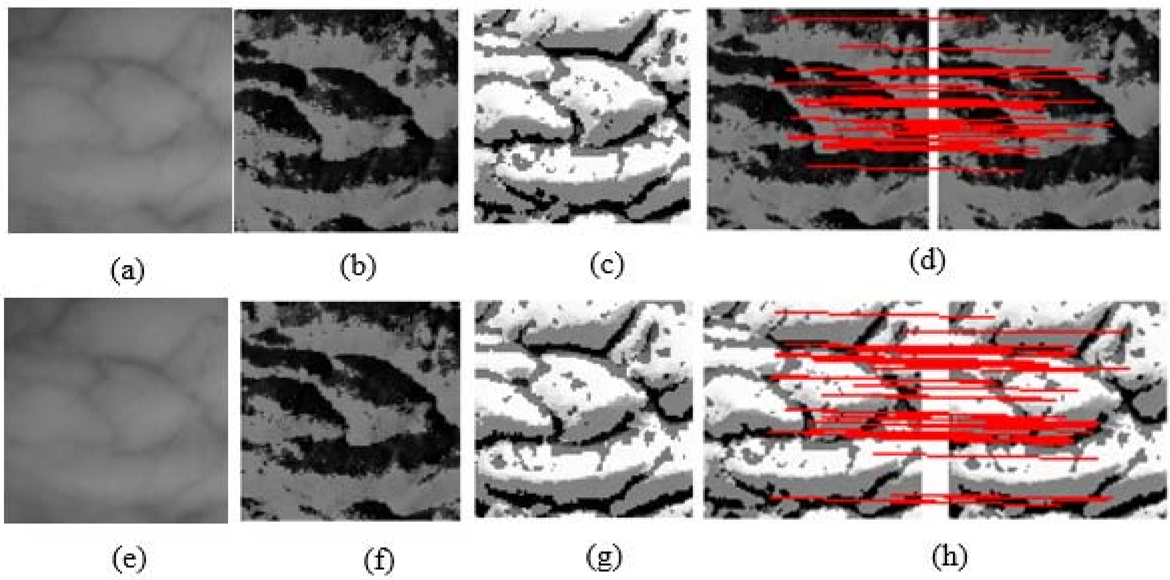

Fig. 3. (a),(e) Original images of the same person, (b),(f) CS-LBP, (c),(g) ECS-LBP, (d) Matching between (b) and (f), and (h) Matching between (c) and (g).

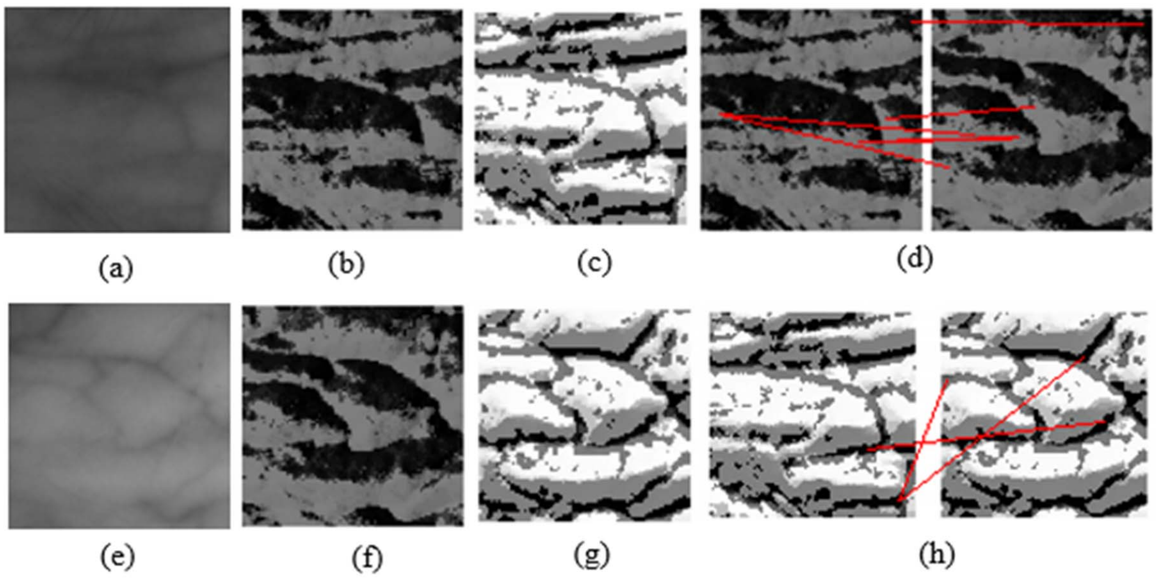

Fig. 4. (a),(e) Original images of two different persons, (b),(f) CS-LBP, (c),(g) ECS-LBP, (d) Matching between (b) and (f), and (h) Matching between (c) and (g).

B. EL-SIFT for detecting palm vein keypoints features and matching

The SIFT feature is the most well-know descriptor that uses a gradient as the local feature. SIFT is a robust method to detect local image features invariant to image scaling, translation, and rotation [40]. These features are obtained by select key locations local maxima and minima of a difference of Gaussian function applied in scale space. Maxima and minima of this scale space function are determined by comparing each pixel to its neighbors [41]. SIFT was applied successfully for palmprint recognition [41]. However, SIFT does not work well with palm vein images because the palm-vein lines do not isolate with low contrast images. (Fig. 3a). In order to create the palm vein patterns with high gradient, ECS-LBP is first applied to get the clear palm vein pattern images. The images are the input of the SIFT algorithm to get the CL-SIFT palm vein key points features (Fig. 3b).

Once the key points are extracted, the query image is matched and compared with each of the features extracted with the corresponding images in the registration database (from the training feature sets). The score generation from the candidate matches is based on Euclidean distance between the feature vectors.

III. EXPERIMENTAL RESULTS

The proposed algorithm has been tested on the public contactless palm vein databases (CASIA Multi-spectral Palm vein Image Database V1.0) [39] for comparison with the previous methods such as LBP [21], CS-LBP-SIFT [18], Gabor-SIFT [37]. Multi-Spectral Palm vein Image Database has been acquired from the contactless palm imaging of 100 users in two data acquisition sessions (three samples in each session) with a minimum interval of one month. Six sub-database in CASIA-Palmvein were acquired under six different wavelength illuminations (460

TABLE I. AVERAGE PERFORMANCE (EER) FROM CASIA LEFT HAND

Matcher	EER(%)	Recognition rate (%)	Time of feature extraction (s)
LBP	8.49	78.33	0.015
Gabor SIFT	3.65	93.67	1.3
CS-LBP-SIFT	4.51	91.33	1.023
Our method: CL-SIFT	3.12	96.33	1.312

TABLE II. AVERAGE PERFORMANCE (EER) FROM CASIA RIGHT HAND

Matcher	EER(%)	Recognition rate (%)	Time of feature extraction (s)
LBP	9.31	77.67	0.016
Gabor SIFT	3.82	91.67	1.287
CS-LBP-SIFT	4.78	90.33	1.015
Our method: CL-SIFT	3.25	95	1.295

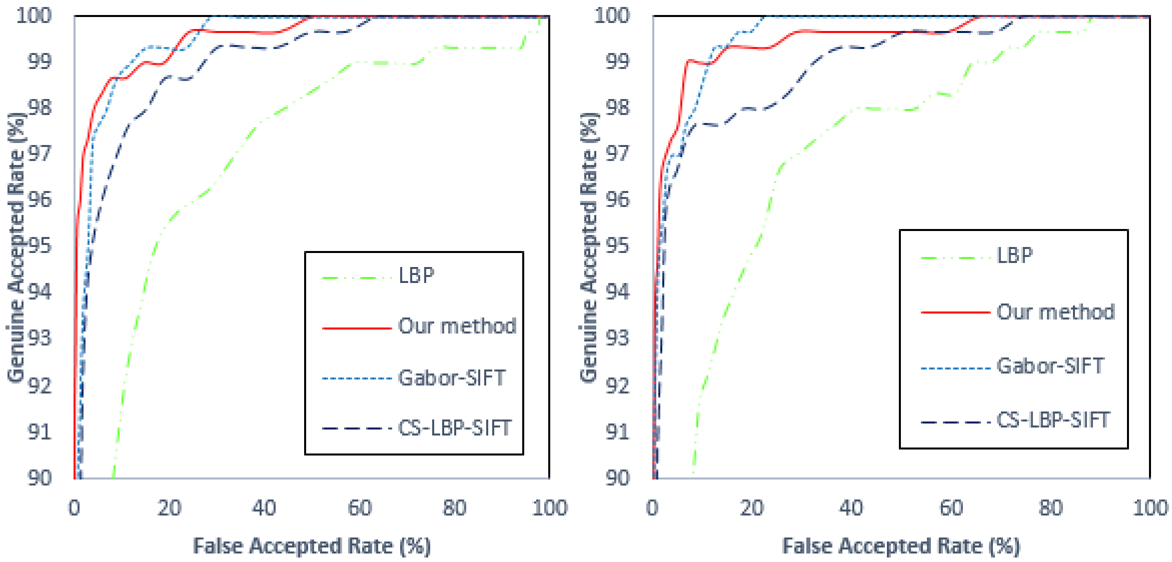

Fig. 5. FAR and FRR for Receiver operating characteristics from the database: (a) left and (b) right palms.

nm, 630nm, 700nm, 850nm, 940 nm, and white light). In CASIA-Palmvein database, we used the images acquired under 850-nm wavelength. The region of interest (ROI) was segmented by using the coordinate system, which is established by two key points (the point between the index finger and middle finger and the point between the little finger and third finger) [1]. Images of size 150 x 150 were cropped out and further resized to 100 x 100.

Identification is a one-to-many comparison that answers the question who is the person in the input image? The rank-1 identification rate is used to compute identification accuracy, in which a test image will be matched with all templates in training set, and the label of the most similar template will be assigned to this test image. Verification is a one-to-one comparison which answers the question of whether the person is whom he claims to be. In experiments, the statistical pairs of False Reject Rate (FRR) and False Accept Rate (FAR) were used to calculate EER [34]. The average rank-1 identification rates from the CASIA-left database and CASIA-right are illustrated in Tables 1 and 2. In our experiments, there are 300 (100×3) genuine scores and 29,700 (100×3×99) imposter scores on both the CASIA left palms database and CASIA right palms database. Fig.5 presents receiver operating characteristics from the CASIA left and right palms databases. The results (see Tables 1 and 2) suggest performance improvement for all approaches.

We implemented all algorithms using java language and tested different descriptors on a VPS with Intel(R) Xeon(R) CPU 2.4GHz 2.4GHz (2 processors) and 4 GB RAM. The simulation time of feature extraction is listed in Table 1 and 2. It can be seen that the feature extraction time of the proposed methods is larger than that of CS-LBP descriptor and smaller than that of Gabor-SIFT.

IV. CONCLUSION

In this paper, we presented an improved SIFT method by proposing combining enhanced center-symmetric local binary pattern (ECS-LBP) with SIFT, called EL-SIFT. ECS-LBP, a modified version of CS-LBP, computes the feature values from blocks (point-sets) instead of the isolated points. The advantage of ECS-LBP is to detect the vein texture stable. The experimental results on the public contactless palm vein databases (CASIA Multi-spectral Palm vein Image Database V1.0) show that our proposed method is more accurate than traditional SIFT methods. Our further research efforts are focused to exploit the orientation information, which can also be simultaneously extracted during contactless palmprint imaging, and develop combination models to effectively apply in more reliable contactless palmprint identification.

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