Extraction of True Palm-dorsa Veins for Human Authentication

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ABSTRACT

This paper presents an efficient system for palm-dorsa vein pattern based recognition system. It can handle efficiently the problem of false palm-dorsa veins which can be created by many ways such as ink, tattoos, artificial vein pattern paper fixed on the palm-dorsa. Hand-dorsa images acquired under visible and infrared lights are used. Since vein pattern from infrared light has spurious and genuine vein pattern, spurious vein pattern is removed from it by using vein pattern from visible light. It has been tested on 600 visible and 600 infrared hand-dorsa images. Experimental results indicate that the proposed system performs efficiently.

Keywords

Palm-dorsa recognition, Biometrics, Fake vein

1. INTRODUCTION

Traditional methods like keys or passwords are not of much use in data protection or security, which allows the access to genuine user while restricting the impostor because these can be easily stolen, lost or spoofed. But this is not the case with biometrics for recognition. It requires individual characteristics having the properties like universality, uniqueness, permanence and acceptability [7]. However, it has been observed that some biometric traits can be spoofed which can fail the authentication system. Spoofing of biometrics has been well studied for various traits like fingerprint, face, iris, speech and gait [20] but it is still in its infancy for the case of vein patterns.

Pattern formed by subcutaneous blood vessels is referred as vein pattern. It is apparent in infrared (IR) light because blood flowing in vein absorbs the IR light. It is a highly useful for personal authentication because it is assumed to be stable, unique and universal [27]. Though it is assumed that vein patterns are hard to forge as these lie inside the skin, it is shown in [18] that one can create fake vein images. Some ways to create fake veins are:

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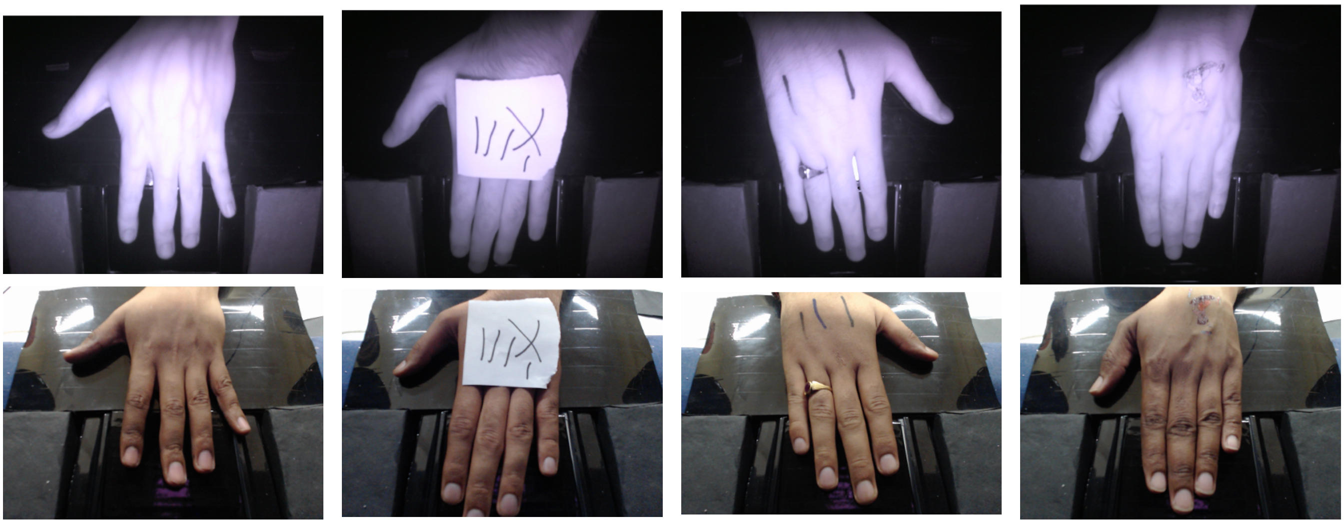
1. One can attach the manually drawn image or vein image on user hand during acquisition to generate fake vein pattern [6]. It is apparent in both visible and IR light. Liveness detection can be used to handle fake vein generation.
2. One can apply any IR light absorbing material on the hand [19] like carbon ink. Since IR light is absorbed, it behaves like vein pattern in IR imagery. Also if its color is different from skin color then it is apparent in visible light.
3. Similarly, area containing hair, tattoo, marks or injury on the user hand, can also be treated as spurious vein pattern which are apparent in both visible and IR light.

These cases are shown in Figure 1. This paper aims to extract the genuine vein pattern from the palm-dorsa image having spurious vein pattern due to tattoo, marks, hairs, carbon ink etc. User data is simultaneously captured using two sensors, viz., IR and visible data acquisition sensors. Acquired IR and visible images are fused by using the intuition that: genuine vein pattern is present in IR image while spurious vein pattern is present in both IR and visible images.

To the best of our knowledge, there is no system which removes the spurious vein pattern generated by tattoo and carbon ink. Some works on spoofed vein pattern detection are shown in [19] and [2]. Both these are applicable only if spoofed pattern is generated by attaching vein image on user hand. System in [19] determines whether an image contains spoofed pattern or not. It is proposed for finger vein pattern. Similarly in [2], multiple veins are captured at different times to determine finger-vein liveness. This is user unfriendly and cost extensive. Also in [22] and [23], palmprint and palm veins are fused for better recognition results but the performance of spoofing has not been studied.

The contribution of this paper is the simultaneous use of IR and visible images for the extraction of accurate genuine vein pattern that improves the recognition results. It also can extract palm-dorsa or region of interest (ROI) from hand image; proposes an accurate vein enhancement by using matched filtering at multiple resolutions; and can detect hand type (either left or right). Hand type detection is not used in any other existing vein based system but it is highly useful to prune out the search space during matching [9].

This paper is organized as follows. Next section presents the literature survey. The proposed system is explained in Section 3. Experimental results are analyzed in Section 4. Conclusions are discussed in the last section.



(a) Normal (b) With Another Image (c) With Carbon Ink (d) With Tattoo

Figure 1: Hand Images in IR (first row) and Visible (second row) Light

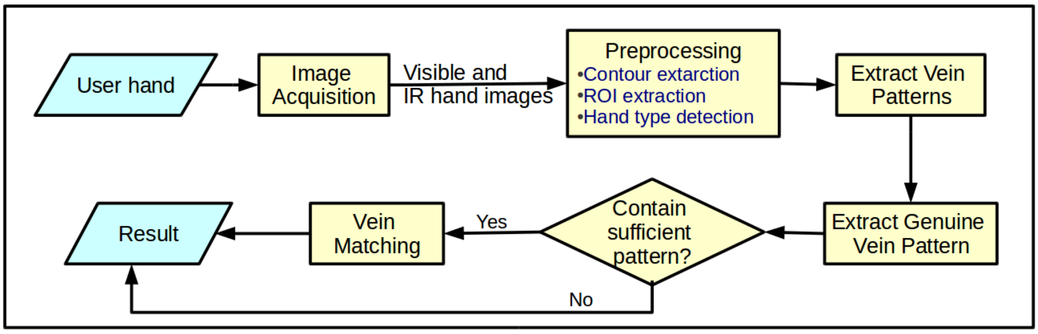


Figure 2: Flow-graph of the Proposed System

2. LITERATURE SURVEY

A vein pattern based biometric system consists of three stages and they are:

1. **Vein Extraction**: Vein images acquired under IR light suffer from the problems of low local contrast, non-uniform illumination and noises due to hairs and texture on human hand. This can generate spurious veins. Thus, vein images are first enhanced by applying various filters like Gabor [15], Steerable [28] and Curvelets [30] filters. Such filters rely on the shape of local neighborhoods of vein pattern and can sometimes result in missing of thin veins. From the enhanced vein images, veins are extracted by using local or global thresholding algorithms [15], [29].

2. **Feature Extraction**: Features extracted from the vein pattern are classified as either local features [17] or shape/ global features. Systems based on local features require some geometrical transformation invariant points while those based on shape features mainly consider full vein pattern or vein skeletons as feature descriptors. Minutiae ending and bifurcation are the most frequently used as local feature. In [21], vein double bifurcation is also used along with minutiae ending and bifurcation. Various minutiae representations like distances between minutiae pairs [24], minutiae triangulations [14] and spectral minutiae [11] can be used as feature representation.

3. **Vein Matching**: Local features are matched by point to point matching either in spatial domain [25], [26] or in frequency domain [12]. Systems relying on local features matching perform poorly because: 1) sometime few local features are available during matching; 2) local features like location of minutiae cannot be accurately determined; and 3) spurious local features can be generated due to noise arise from hairs, texture or environmental conditions. On the other hand, matching of shape feature can be accurately localized and can handle the occlusion. But required features have large dimensionality which can be reduced by using invariable moments [16] and machine learning techniques [13]. It can lead to loss of useful information and thus has low discriminatory power. Some systems avoid dimensionality reduction by using pixel-by-pixel matching [1] and correlation matching [5].

3. PROPOSED SYSTEM

In this section, an efficient recognition system for palm-dorsa veins has been presented which can effectively handle the spurious veins. Flow-graph of the proposed system is shown in Figure 2.

3.1 Image Acquisition

A hand of a subject is placed on a fixed black peg-free plank without any constraint on finger orientation. Its hand-dorsa area is acquired from two color cameras fixed above the plank such that complete hand can be captured. In front of one color camera, an IR filter is attached which makes it useful for acquiring the IR images while the other one acquires image in visible light. Human hand can emit IR radiation of 3000-12000 nm which cannot be properly acquired by the camera hence it is irradiated by an IR lamp of 850 nm. Let images acquired color and IR camera be represented by I_C and I_I respectively. Acquisition setup along with hand image in IR light and in visible light is shown in Figure 3. Since it does not contain pegs or any other docking device, it is regarded as unconstrained. Further, there is no direct contact between sensors and finger which makes it a touch-less system.

Algorithm 1 $Preprocessing(I_C)$

Require: Hand image, I_C
Ensure: Return $HandType$ and I_C^R storing hand type and extracted ROI respectively.

I_B = global_threshold_algorithm(I_C) //Binarized image
Remove holes and small sized components from I_B.
B_h = canny_edge_detector(I_B) //contains contour
Find key-points by applying contour tracing algorithm on B_h.
Detect $HandType$ (left or right) by using hand geometry constraints on key-points.
Find end points of thumb and left finger.
Fingers are removed from I_B by using key-points to detect the ROI, I_C^R.
return ($HandType$ and I_C^R)

3.2 Preprocessing

In this section, palm-dorsa or region of interest (ROI) is extracted and hand type (whether left or right) present in I_C is detected. Hand is localized in I_C by using global thresholding algorithm followed by 8-neighborhood connectivity algorithm [8] because black plank can be easily differentiable from skin color. Detected hand area may contain isolated small blobs or holes due to hair present on the hand-dorsa, which are removed by using standard morphological operations [10]. Canny edge detector is applied on binarized image to extract the contour (or boundary) of hand, say B_h.

As finger area in acquired IR image is devoid of useful finger vein information, these are removed to obtain the ROI. It requires valley points between alternating fingers that can be found by local minima in B_h; and fingertips of each finger that can be determined by local maxima in B_h. Detected key-points are used to determine the hand type by using the intuition that the number of boundary points between the fingertips of thumb and index finger is greater than the number of boundary points between the fingertips of ring and little finger. We have used two additional key-points for ROI extraction. These key-points are the end points of little finger and thumb. These are found by using the intuition that both the end points of a finger are equidistant from its fingertip. Using these detected key-points, fingers are cropped to extract the ROI. Figure 4 shows the marked key-points, extracted ROI and few examples corresponding to Figure 3(b) and Figure 3(c). In it, valley points, fingertips and additional key-points are shown in blue, red and green color respectively. Let I_C^R represents the extracted ROI from I_C. Similarity ROI corresponding to I_I is extracted and let it be represented by I_I^R. Steps involved during preprocessing are given in Algorithm 1.

Algorithm 2 $Vein\_Pattern\_Extraction(I_I^R, G_1, G_2)$

Require: Palm-dorsa image, I_I^R, and filters G_1 and G_2 at different scales.
Ensure: Return V_{SG} containing vein pattern.

$R_g^{s_1} = G_1 \otimes I_I^R$
$R_g^{s_2} = G_2 \otimes I_I^R$
// $\otimes$ is the convolution operation
for each pixel (x,y) **do**
  $M(x,y) = \left(R_g^{s_1}(x,y) \times R_g^{s_2}(x,y)\right)$
end for
I_B = global_threshold_algorithm(M)
//Binarized image containing vein pattern
Remove holes and small sized components from I_B.
B = canny_edge_detector(I_I^R) // B stores hand contour
for each pixel (x,y) **do**
  $V_{SG}(x,y) = I_B(x,y) \curlywedge (\neg B(x,y))$
  /* where $\neg$ and $\curlywedge$ are negation and binary AND operation respectively. These are used to remove boundary pixels from I_B to form V_{SG}.*/
end for
return V_{SG}

3.3 Vein Pattern Extraction

Due to low contrast and non-uniform illumination in I_I^R, it is enhanced by using following observations: i) cross sectional profile of vein is nearly gaussian; ii) vein has almost line shaped structure; and iii) multi-resolution analysis helps to enhance effectively the variable width veins. Thus, a vein shaped filter ([3]), G_ϕ, can be used at multiple resolutions. It has two orthogonal directions; one has gaussian shape of standard deviation σ and mean m while other has line shape of length l. It is evaluated at each pixel (x,y), orientation ϕ and scale s by using

$$G_{\phi,s}(x,y) = \begin{cases} -e^{\left(\frac{-p^2}{s\sigma_x^2}\right)} - m & \text{, if } |p| \le 3s\sigma_x \text{ and } |q| \le \frac{sl}{2} \\ 0 & \text{, otherwise} \end{cases}$$

where

$$p = x\ cos\phi + y\ sin\phi$$

$$q = y\ cos\phi - x\ sin\phi$$

Filter response of I_I^R at a scale s is given by

$$R_g^s(x,y) = G_{\phi,s}(x,y) \otimes I_I^R(x,y)$$

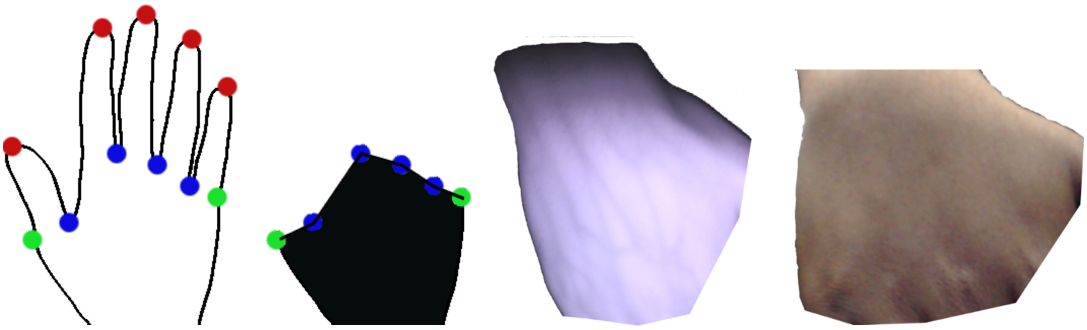
where $\otimes$ denotes the convolution operator. Filter responses calculated at two scales, s_1 and s_2, are consolidated by:

$$M = \left(R_g^{s_1} * R_g^{s_2}\right)$$

where M and $*$ denote the multi-scale matched filter response and the element-wise product operation respectively.

(a) Setup (b) Image in IR light (c) Image in visible light

Figure 3: Image Acquisition



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

Figure 4: ROI Extraction

Vein pattern is extracted from the enhanced image M by applying global thresholding algorithm. It contains isolated holes due to noises or hairs on palm-dorsa, which are removed by using morphological operations. Further, spurious vein pattern can be formed near the boundary of I_I^R which can be removed by using boundary information. Let extracted vein pattern be V_{SG}. Steps used for vein extraction are given in Algorithm 2. Similarly, one can extract vein pattern present in I_C^R, V_S. As vein pattern extracted from color image generally gives spurious vein information, V_S gives the spurious vein pattern present in palm-dorsa. Some examples of extracting the genuine vein pattern are shown in Figure 5.

3.4 Genuine Vein Pattern Extraction

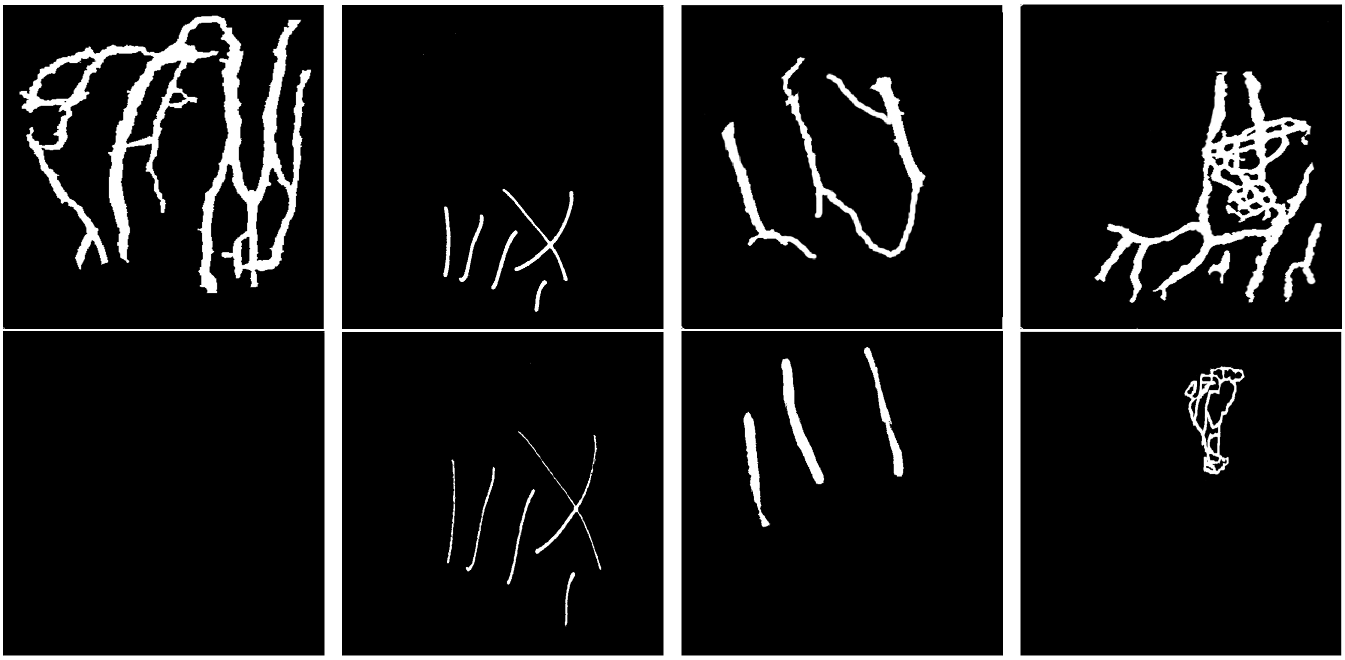
Since V_{SG} contains both genuine and spurious vein pattern while V_S contains only spurious pattern, genuine vein pattern can be obtained by removing V_S from V_{SG}. This requires registration of V_{SG} and V_S. The acquisition setup is made in such a way that locations of plank and cameras are fixed. Thus, the homography matrix required for transforming the images from color image to IR image is fixed. It is determined by using camera calibration [22]. It registers V_{SG} and V_S but there can be small misalignment. It can result in introducing small errors while removing V_S from V_{SG} thus it is dilated. Genuine vein pattern, V_G is extracted by using

$$V_G(x, y) = V_{SG}(x, y) \curlywedge (\neg V_S(x, y)) \tag{1}$$

where (x, y) is the pixel location while $\neg$ and $\curlywedge$ are negation and binary AND operation respectively. V_G may contain unnecessary breaks due to hair; thus, V_G is dilated. Algorithm 3 describes the steps involved during genuine vein pattern extraction. It is possible that V_G contains no or less vein pattern due to: (i) genuine veins being interfered or covered by spurious veins [19]; or (ii) skin and environmental conditions. Vein matching of such cases may provide meaningless or erroneous information. Thus, if the number of genuine vein pixels in V_G is less that a predefined threshold then, V_G is not used for vein matching. Some examples are shown in Figure 6.

3.5 Vein Matching

Let the stored template, U_G needs to be matched with V_G to verify the user identity. In this, U_G and V_G should have same hand type. Our acquisition setup can cause large translation and rotation transformation in the acquired hand image but it cannot introduce large nonlinear deformations. Further, there are possibilities of: (i) missing of some part of genuine vein pattern; and (ii) generation of spurious vein pattern. Reasons for these are noise (due to skin texture



(a) Normal (b) With Another Image (c) With Carbon Ink (d) With Tattoo

Figure 5: Extracted Vein Pattern of Images shown in Figure 1

(a) Normal (b) With Another Image (c) With Carbon Ink (d) With Tattoo

Figure 6: Genuine Vein Extraction of Images shown in Figure 1

Algorithm 3 $Genuine\_Vein\_Pattern(V_{SG}, V_S, H)$

Require: V_{SG} and V_S which are vein patterns extracted from images captured in IR and visible light along with homography matrix H.

Ensure: Return genuine vein pattern, V_G

1: Register V_S with respect to V_{SG} by using H and dilate it.
2: **for** each pixel (x,y) **do**
3: $V_G(x, y) = V_{SG}(x, y) \curlywedge (\neg V_S(x, y))$
/* where $\neg$ and $\curlywedge$ are negation and binary AND operation respectively. */
4: **end for**
5: Dilate V_G
6: **return** V_G

or hairs), non-uniform illumination and low local contrast [27]. Thus, V_G is registered with respect to U_G by using Fourier-Mellin transform based image registration [4] which is robust against noise, occlusion, translation, scaling and rotation. In [4], log-polar transformation on spectral magnitude is used to transform the rotation and scaling into translation. Eventually, all registration parameters are estimated by using phase correlation. Let registered image of V_G with respect to U_G is represented by R. Similarity score between U_G and V_G, s_{uv}, is given by

$$s_{uv} = \frac{\sum_{x,y} R(x, y) \times U_G(x, y)}{max\left\{\sum_{x,y} R(x, y), \sum_{x,y} U_G(x, y)\right\}} \quad (2)$$

where (x, y) represents a pixel location while max is the maximum operator. If s_{uv} is greater than the preassigned threshold then U_G and V_G are considered to be matched. Steps followed during the proposed vein matching are shown in Algorithm 4.

Algorithm 4 $Vein\_Matching(V_G, U_G, th)$

Require: V_G and U_G containing sufficient genuine vein patterns and a threshold th required for matching decision.

Ensure: Return whether U_G and V_G are matched or not matched in D.

1: Register V_G with respect to U_G and let it be R.
2: $s_{uv} = \frac{\sum_{x,y} R(x,y) \times U_G(x,y)}{max\{\sum_{x,y} R(x,y), \sum_{x,y} U_G(x,y)\}}$
3: **if** $s_{uv} \leq th$ **then**
4: $\quad D = not\ matched$
5: **else**
6: $\quad D = matched$
7: **end if**
8: **return** D

4. EXPERIMENTAL RESULTS

Since there is no publicly available database for fake palm-dorsa, we have created four databases to evaluate the performance of the proposed system. Each of these has 150 IR and 150 visible light palm-dorsa images of size 2304×1536 pixels from 30 different classes, i.e., 5 IR and 5 visible images from each class. Thus, total 600 IR and 600 visible light palm-dorsa images are used for evaluation. Correct recognition rate (CRR) and equal error rate (EER) are used as metrics for evaluating the performance of the system.

4.1 Database 1

Its images do not contain any spurious vein pattern. Its example is shown in Figure 1(a). Images for a same class are acquired after an average time gap of 1 minute. For testing, one genuine vein pattern corresponding to each user is used in a gallery set while another four genuine vein patterns are used as probe set. Thus, there are 3,600 (30×120) matchings. The proposed system has achieved a CRR of 100% with an EER of 0%. Its comparison with other well known systems is shown in Table 1. It can be seen that the proposed vein system outperforms various well known systems, even if the vein images do not contain spurious veins. Receiver operating characteristic (ROC) curve corresponding to the Table 1 is shown in Figure 7(a). Reason behind this are:

1. In [25] and [21], minutiae are used as features which cannot be accurately localized or detected. In addition, sometime minutiae can be occluded or spuriously generated due to noise. System [21] performs better than system [25] due to better feature matching.

2. The proposed system has better results than [1] because it uses better vein extraction based on multi-scale matched filtering.

Table 1: Comparative Results on Database 1

System	CRR	EER
[25]	86.66%	9.79%
[21]	92.66%	4.36%
[1]	95%	2.51%
Proposed	**100%**	**0%**

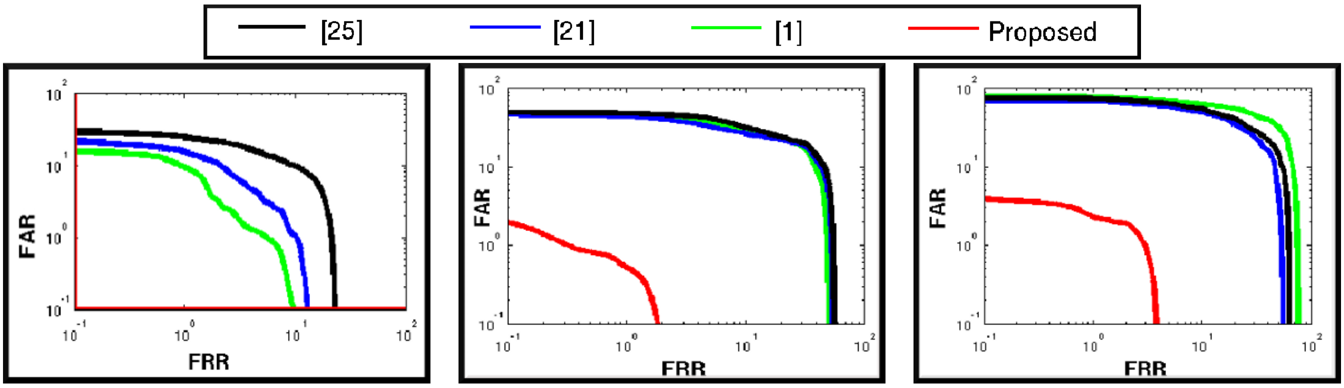
4.2 Database 2

To test the effectiveness against the attempt to spoof the system by pasting an artificial image on the hand, Database 2 has been created. There are five data acquisition for each class in Database 2 such that during the first two acquisitions, palm-dorsa is first covered by a paper which has manually drawn vein pattern (for example, consider Figure 1(b)) while during the remaining data acquisitions, palm-dorsa is covered by a gray-scale vein image. Since attaching and detaching an image on palm-dorsa takes time, average time gap between data acquisition of same class is approximately 4 minutes. It has been found out that no genuine vein pattern is extracted by the proposed system in such cases. It is because fake veins are accurately extracted from the visible image and marked as a spurious vein pattern by the proposed system. Hence, the proposed system can accurately handle such cases of fake vein pattern. Due to less number of genuine vein pixels, these are not used for vein matching. When [19] is applied on Database 2, it is observed that system [19] also gives accurate results. But it requires: (i) large training data for SVM; and (ii) prior knowledge of the image attached on palm-dorsa. On the other hand, other well known systems have spuriously extracted the vein pattern and results in wrong vein matching.

4.3 Database 3

It has been created to study the effect of ink on user hand. Ink is applied on palm-dorsa by drawing some line shaped pattern which look like veins. To understand the impact of such spuriously generated veins on vein matching, ink is completely removed after each acquisition and veins like lines are drawn again for subsequent acquisition. Due to this time consuming process, images of a same class are acquired after an average time gap of 6 minutes. These image pairs have both genuine and spurious vein patterns such that spurious veins generated due to ink are apparent in visible images. It can be visualized from Figure 1(c). It is observed that the proposed system accurately extracts the genuine vein patterns. But there are some genuine vein pattern areas on which ink is applied and these areas could not be detected. Further, blue color ink is not visible in IR images and thus, it has no effect. Corresponding to each user, one genuine vein pattern is used in gallery set while other genuine vein patterns are used in probe set for vein matching. The proposed system has a CRR of 99.33% with an EER of 0.75%. In addition, if vein matching is applied without removing the spurious vein pattern, then CRR is 77.12% with an EER of 15.32%. It points out that if fake vein pattern generated due to ink are removed then recognition results can be significantly improved. Table 2 shows the comparison of the proposed system with other well known systems on Database 3. ROC curves corresponding to it is shown in Figure 7(b). It can be seen that the proposed vein system outperforms various well known systems when ink is applied on human hand. It is because ink generates false features like false minutiae in case [25] and [21] while false veins in case of [1]. One important observation from Table 2 is that there are some spurious cases even if the proposed system is used. Such cases are generated if ink is applied in large proportion which can lead to occlusion of genuine vein pattern.

4.4 Database 4



(a) Database 1 (b) Database 3 (c) Database 4

Figure 7: ROC Curves

Table 2: Comparative Results on Database 3

System	CRR	EER
[25]	70.33%	22.58%
[21]	73.33%	21.82%
[1]	71.66%	21.91%
Proposed	**99.33%**	**0.75%**

Table 3: Comparative Results on Database 4

System	CRR	EER
[25]	61.66%	29.61%
[21]	62.33%	27.18%
[1]	53.66%	39.84%
Proposed	**98.66%**	**1.95%**

In order to study the effect of tattoos, Database 4 is created whose images are acquired after applying temporary tattoo on palm-dorsa. One such acquired sample is shown in Figure 1(d). It has been observed that the edges which have black color in the tattoo design resemble veins and thus form a spurious vein pattern. But these spurious vein patterns are present in both IR and visible images. It is observed that the proposed system accurately extracts the genuine vein patterns, except at the areas which are overlapping with spurious vein pattern. It gives a CRR of 98.66% with an EER is 1.95%. While if vein matching is applied without removing the spurious vein pattern generated due to tattoo then CRR is 64.33% with an EER of 26.48%. Reasons for low CRR and high EER are: (i) some tattoos applied on different hands have similar designs; and (ii) some tattoos applied on same hands have different designs. It indicates that the proposed system is highly useful for accurate vein pattern recognition in case of temporary tattoos. Table 3 shows the comparison of the proposed system with other well known systems on Database 4. Its ROC curve is shown in Figure 7(c). It illustrates that the proposed vein system outperforms other well known systems when a tattoo is applied on human hand. It occurs because false minutiae generated in [25] and [21], and false veins generated in [1] are referred as genuine features during matching which result in spurious vein matching results. In addition, sometime large area of genuine vein pattern is occluded by the tattoo due to which even the proposed system may give spurious results.

4.5 Discussion

It can be inferred that the proposed system performs better than various well known vein biometric based systems, especially if spurious veins are present in the acquired image. Spurious veins can tremendously deteriorate the effectiveness of vein based biometric system and thus it should be suitably handled. Also, it is observed that if fake veins are generated by attaching vein image on user hand, then one can also use the system in [19]. Further, system in [2] requires highly expensive data acquisition setup and is highly user unfriendly, thus, it is avoided. Hence, the proposed system which removes spurious veins by using the information from visible image is highly useful to achieve better performance.

5. CONCLUSION

This paper has presented the system to handle the effect of fake vein patterns so that one can create an accurate recognition system by using palm-dorsa. Fake vein patterns can be generated if a user hand contains ink, tattoo or a vein image. These have been studied and their impact under visible and IR light are used to extract the genuine vein pattern. It is designed based on the intuition that such fake vein patterns are visible in visible and IR light while genuine patterns are visible only in IR light. Vein patterns have been accurately extracted by using matched filtering at multiple resolutions. Vein pattern corresponding to visible light (spurious vein pattern) has been removed from the vein pattern corresponding to infrared light (spurious and genuine vein pattern) to accurately obtain genuine vein pattern. We have tested the proposed system on a database of 600 visible and 600 infrared hand-dorsa images by introducing different type of fake palm-dorsa vein images. Experimental results have revealed that it can accurately eradicate the false vein pattern. Further, it has shown that the recognition results can be improved substantially if fake veins are removed.

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