Multibiometric Authentication System Using Slap Fingerprints, Palm Dorsal Vein, and Hand Geometry

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***Abstract*—In this paper, a multibiometric system that fuses slap fingerprints, palm dorsal vein, and hand geometry for accurate person authentication is proposed. The proposed system simultaneously acquires slap images and infrared (IR) hand dorsal image from which slap fingerprints, palm dorsal veins, and IR hand geometry are extracted. Simultaneous acquisition reduces the acquisition time and helps to improve user acceptability. The slap segmentation is accomplished using the knowledge of the approximate finger location and hand type (either left or right) obtained from the simultaneously acquired IR hand dorsal image. Multibiometric fusion based on serial methodology has been proposed for consolidating the matching scores of slap fingerprints, palm dorsal vein, and IR hand geometry. It ensures better performance in terms of accuracy and time. Experimental results indicate that authentication using slap fingerprints can be improved by incorporating the knowledge from IR hand images. Further, it depicts that the fusion of slap fingerprint, palm dorsal vein, and IR hand geometry can help to achieve the best performance.**

***Index Terms*—Authentication, hand geometry, multibiometric system, palm dorsal vein, slap fingerprint.**

I. Introduction

PERSON authentication system is a prime requirement in the modern scenario due to the rapid evolution in hardware and software technology. Traditional authentication mechanisms based on keys or password are insufficient because they can be easily guessed, duplicated, transferred, or misplaced. The efficacy of an authentication system relying on a single trait is restricted due to sensor noise, improper user interaction, environmental conditions, and the properties of the involved trait [1]. Hence, multiple traits can be fused to enhance the performance of the system. But such type of systems, multibiometric system, require large acquisition time, which decreases the user acceptability. Thus, one should select such type of traits in the multibiometric system, which can minimize the time. In this paper, a multibiometric authentication system, which makes use of three biometric traits viz., slap fingerprints, palm dorsal vein, and infrared (IR) hand geometry, has been proposed. A slap image contains all the single fingerprints present in a hand. All single fingerprints, referred as slap fingerprints, can be segmented and used for authentication [1]. Palm dorsal vein is the hypodermic blood vessels present in the palm dorsal, i.e., the area at the back side of the palm.

Fingerprint is extensively used for authentication due to its uniqueness and invariance with time. But such authentication can be erroneous when bad quality fingerprints are acquired due to environment factors, user factors, and sensor condition. Performance can be enhanced and spoofing can be made more difficult by incorporating all fingerprints of a hand, i.e., utilizing slap images [2]. A slap fingerprint authentication system consists of image acquisition, segmentation, and matching. In segmentation, single fingerprints present in the slap image are extracted and labeled as index, middle, ring, or little finger of left/right hand. Each labeled fingerprint is matched to the appropriate template to generate a matching score and all the matching scores are fused for authentication. If single fingerprints are erroneously extracted or labeled, wrong single fingerprints are matched that degrades the system performance. Hence, slap segmentation plays a crucial role in the authentication. In slap segmentation, the hand pixels are separated from the background pixels using anisotropic measures because hand pixels contain large intensity variations as compared to the other pixels [2]. They are coalesced by neighborhood connectivity to form *components*. The components are clustered such that components derived from same finger are clustered together. There exist the possibilities of wrong clustering due to noise in background and improper orientation [2]. The topmost component from each finger (or class) is marked as fingerprint component as fingerprint lies at the top of a finger. Hand geometry constraints are used to number the fingerprints according to their left to right placement in a hand and detect whether left or right hand is present in the slap image [3]. These are not useful when the hand is inappropriately placed.

Palm dorsal vein trait is being contemplated as a competent biometric trait satisfying all the requirements of a trait along with the following benefits.

1) It lies inside the skin, which makes spoofing difficult.

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2) It can be acquired in a contact-less manner, which makes it more user friendly.
3) It assures liveness.

In these systems, veins are extracted from palm dorsal images by making use of the following properties.

1) The cross section of a vein looks like a Gaussian shape.
2) A vein looks like a line in the tangent direction.
3) Veins do not have a fixed width.

One such vein extraction that incorporates all these properties is based on multiscale matched filtering and the extracted vein pattern is used to match for authentication either by local feature matching or by shape matching [4]. Often the local feature matching fails to provide accurate matching when a few local features are available from the extracted vein pattern. Similarly, global feature or shape matching may become spurious when scaling or nonrigid deformations are introduced in the acquired image.

IR hand geometry is beneficial for authentication because of the following reasons.

1) It is possessed by most of the users.
2) It can be easily acquired.
3) It is found to be moderately distinctive for authenticating small population [5].
4) It can be fused with other traits to enhance the performance [4].

Hand geometry acquisition in visible light is avoided because it suffers from the problem of varying backgrounds and illumination conditions [4]. IR images lack texture [6]; hence, IR hand geometry systems avoid texture matching. Often, these systems segment the fingers; label them as index, middle, ring, or little finger and use their geometrical properties such as finger lengths and finger widths for authentication [4].

Reasons for the use of slap fingerprint, palm dorsal vein, and IR hand geometry in the proposed system are that these traits provide good authentication and these can be simultaneously acquired. The main contributions of the paper are as follows.

1) To the best of our knowledge, this is the first attempt that fuses slap fingerprints, palm dorsal veins, and IR hand geometry for authentication. A major factor that limits the use of several biometric traits in authentication is the lack of simultaneous acquisition system. We have designed an acquisition setup that allows us to acquire all three traits simultaneously.
2) Slap fingerprint segmentation is one of the crucial factors in deciding the efficacy of slap-fingerprint-based authentication system. It requires the knowledge of finger locations and hand type (left or right hand) for accurate extraction and labeling of single fingerprints. In the absence of such type of knowledge, several hand geometry constraints are used, which may fail due to several reasons. Fortunately, the knowledge of finger locations and hand type can be gathered from the IR image, which is also acquired along with the slap image. In this paper, a slap fingerprint segmentation based on knowledge transfer has been proposed for better authentication.
3) Multibiometric fusion based on serial methodology has been introduced for consolidating the matching scores of slap fingerprints, palm dorsal vein, and IR hand geometry. The proposed fusion avoids the unnecessary matching of palm dorsal veins and IR hand geometry in several cases, which results in less computational time.

The outline of this paper is as follows. Section II discusses about biometric fusion and knowledge transfer, which are the basis of the proposed system. The proposed multibiometric system is described in Section III. Experimental results are analyzed in Section IV. Conclusions are given in Section V.

II. Literature Survey

A. Biometric Fusion

Different biometrics can be fused with the help of either parallel or serial fusion strategy. In parallel fusion, all selected traits are utilized simultaneously for authentication [7]. But serial fusion employs one trait at a time for the authentication and if the considered trait is incapable of providing the correct authentication, another trait is utilized. This procedure of considering another trait continues till correct authentication can be found or no other trait is available for authentication [8]. Since it avoids the unnecessary matching of biometric traits, it performs faster authentication as compared to parallel fusion [9]. Fusion can be done at various levels such as feature level, score level, and decision level [10]. In feature level, features corresponding to the traits are fused and used for matching. It is useful when the traits considered for fusion provide same type of feature characteristics [11]. However, when the traits utilized in the fusion are independent then usually score- and decision-level fusions are used [12].

B. Knowledge Transfer

Usually any problem is solved first by mapping it to previously seen similar problems and then the experiences gained while solving the similar problems in the form of findings, challenges, and solutions are used to solve it. Such an inherent mechanism to use the knowledge gained from the seen problems (known as source tasks) to solve a new problem (known as target task) is referred as knowledge transfer [13]. It consists of the four steps viz., source determination, knowledge extraction, knowledge mapping, and solving target task. In the first stage, source domain is selected such that source and target domains are highly correlated. But if there is less correlation, the performance can be degraded and such knowledge transfer is referred as negative transfer. In the next stage, appropriate features or knowledge is extracted from the source domain using the relationship such that the positive transfer is maximized, whereas the negative transfer is minimized. Subsequently, knowledge gathered from the source domain is mapped so that the target task can make use of it. Eventually, a mechanism should be properly defined, which aims to solve the target task using the mapped knowledge.

III. Proposed System

In this section, an authentication system that fuses slap fingerprint, palm dorsal veins, and IR hand geometry is proposed. It consists of three stages viz., image acquisition, segmentation, and multibiometric fusion. In the first stage, an acquisition

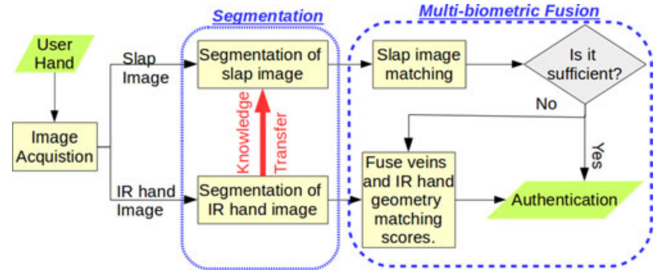
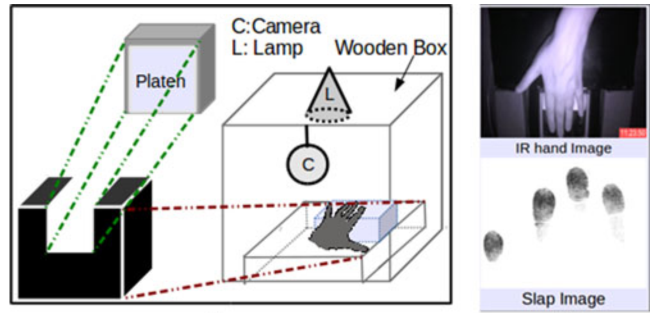
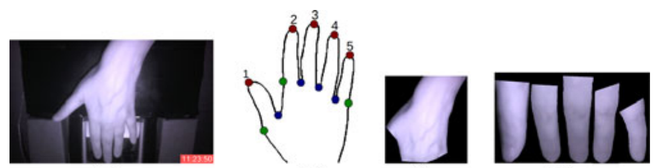


Fig. 1. Flow graph of the proposed system.



(a) (b)

Fig. 2. Description of image acquisition. (a) Setup. (b) Example of simultaneously acquired slap image and IR hand dorsal image.



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

Fig. 3. Illustration of the IR hand dorsal image segmentation. These depict (a) an acquired IR hand dorsal image, (b) example of stable and key points, (c) segmented palm dorsal, and (d) segmented fingers.

system is presented that simultaneously acquires the IR hand dorsal image and the slap image. In the next stage, palm dorsal veins and IR hand geometry are extracted from the hand dorsal image, whereas slap fingerprints are extracted from the slap image. In the last stage, serial fusion of slap fingerprint, palm dorsal veins, and IR hand geometry is performed. The flow graph of the proposed system is shown in Fig. 1.

A. Image Acquisition

This section presents an acquisition setup that can simultaneously acquire slap fingerprint, palm dorsal veins, and IR hand geometry. It requires an IR lamp and two acquisition sensors viz., slap scanner to acquire slap image and a low-cost camera to acquire palm dorsal veins and IR hand geometry. Unfortunately, a human hand emits the IR radiation in the range of 3000–12 000 nm, which cannot be analyzed by the low-cost camera. Thus, an IR lamp emitting the IR radiations of 850 nm is used to irradiate the human hand. An IR filter is placed in front of the camera to minimize the interference of visible light. The glass on the top of a slap scanner is referred as platen. The area of user hand touching the platen is acquired in the slap image; thus, the user should place all the fingertips of a hand on the platen.

The setup is covered from all sides using wooden walls except one from which a user can look inside the setup and place the hand. At the bottom of the setup, a black color plank and slap scanner are placed. To ensure the presence of all single fingerprints in the acquired slap image, users are advised to place their hands in an unconstrained manner such that all the hand fingertips should touch the platen and the remaining hand rests on the platen. Moreover, the hand dorsal should be properly illuminated to acquire the images in IR light. Hence, an IR lamp is placed at the top of the setup to illuminate uniformly the plank and the platen, which in turn illuminate the full hand dorsal placed on them. The illuminated hand is acquired by placing the camera at the top of the setup in such a way that it is capable to acquire the full plank and the platen. The proposed acquisition system is shown in Fig. 2 along with an acquired biometric sample. Change in the camera parameters (such as focal length and exposure time) and relative positions between plank, slap scanner, camera, and IR lamp can deteriorate the efficacy of palm dorsal vein and IR hand geometry matching, thus, these parameters are maintained in the acquisition setup.

B. Segmentation

In this section, the process of extracting fingers and palm dorsal from IR hand image and subsequently single fingerprints from slap image has been discussed. The segmentation of IR hand image requires hand geometry constraints for the accurate extraction. The fingerprint extraction uses hand geometry constraints along with the knowledge provided by the location of the extracted fingers.

1) Segmentation of IR Hand Images: There is a clear separation among the pixels of the black plank and the remaining pixels. Hence, global thresholding is used to detect the pixels of plank [4]. Components in the resultant image are detected using eight-neighborhood connectivity [1]. It is intuitive that the component belonging to a hand contains the largest area as compared to the other components generated due to platen. Thus, the largest component is detected and marked as a hand component. It may contain isolated small holes that can be filled by the standard morphological operations.

The segmentation of the localized hand into palm dorsal and localized fingers requires two types of stable points viz., the topmost point from each fingertip and the valley point between the alternating fingers. The topmost and valley points are given by local minima and local maxima of a hand silhouette, respectively [4]. The hand silhouette is estimated by applying Canny Edge detector on the localized hand image. For simplicity, the thumb is also considered as a finger. For the segmentation, three additional key points are also required viz., end points of little finger, index finger, and thumb. These are determined using the fact that the end points of a finger are equidistant from the fingertip. The line sweep algorithm proposed in [2] is used to number topmost points as 1–5 based on their left to right placement in a hand, as shown in Fig. 3(b). Hand type (either left or right) present in the image is determined using the intuition that the total number of boundary pixels between the topmost points of thumb and index finger are more than the number of boundary pixels between ring and little fingers. In other words, if the total number of boundary pixels between the topmost points 1 and 2 of Fig. 3(b) is greater than the total number of boundary pixels between the topmost points 4 and 5, the image is of right hand, otherwise it is of left hand. These boundary pixels are given by contour tracing [4]. The numbering and hand type are used to label the topmost points as either thumb, index finger, middle finger, little finger, or ring finger. Similarly, valley points are also labeled using the topmost points labeling and hand anatomy. The locations of each finger and palm dorsal are determined using all the labeled additional key points and stable points. An example of the proposed IR hand dorsal segmentation is shown in Fig. 3. Valley points, topmost fingertip points, and key points are shown in Fig. 3(b) using blue, red, and green colors respectively.

2) Knowledge-Transfer-Based Slap Segmentation: Slap segmentation can be failed if the slap image contains halo, sweat, or improper orientation [3]. These issues can be resolved if finger locations are known, but the locations cannot be estimated by merely using the slap image. Fortunately, IR hand images simultaneously acquired with the slap image can provide the accurate location of fingers to resolve these issues and improve the segmentation. Based on this, a knowledge transfer algorithm is proposed for slap segmentation, which consists of the following steps.

1) *Determine source domain*: In the knowledge transfer, an IR hand image simultaneously acquired with the slap image is used as a source domain, whereas the extraction of single fingerprints from the slap image defines the target task. Such a source domain is chosen because simultaneously acquired IR hand image and slap image are highly correlated in the sense that they both provide similar locations of fingers and hand present in the image.
2) *Extract knowledge*: Finger locations extracted during the segmentation of IR hand images are transferred as knowledge. Four binary images are created corresponding to each finger such that each image contains 1 at the locations of the labeled finger and 0, otherwise.
3) *Knowledge mapping*: The finger locations in simultaneously acquired IR hand image and slap image are correlated in the sense that they are acquired from a same hand at a same time. Yet they are somewhat different as they are acquired from different viewpoints and sensors. Hence, this knowledge or locations provided by source domain should be properly transferred or mapped. It is important to remember that the relative positions between plank, slap scanner, camera, and IR lamp are maintained in the acquisition setup throughout the data acquisition. The constraint ensures that the homography matrix required to transform the pixel location in an IR image to the pixel location in a slap image is fixed in all cases. It can be estimated *a priori*. Let H be the 3×3 homography matrix given by
$$H = \begin{bmatrix} a & b & t_x \\ c & d & t_y \\ p_1 & p_2 & 1 \end{bmatrix} \tag{1}$$
where (a, b, c, d) are the rotation, scaling, and shearing parameters; (t_x, t_y) are the translation parameters; and (p_1, p_2) are the projection parameters required for perspective transformations [14]. In order to transform the finger locations from the source domain to the locations in the target domain, each pixel (x, y) in the binary images is transformed by applying
$$x' = \frac{ax + by + t_x}{p_1 x + p_2 y + 1} \quad ; \quad y' = \frac{cx + dy + t_y}{p_1 x + p_2 y + 1} \tag{2}$$
where (x', y') denotes the transformed location of the pixel (x, y), whereas $a, b, c, d, t_x, t_y, p_1,$ and p_2 are the parameters given by H. Moreover, the resultant transformed binary images are dilated to compensate for the small camera calibration errors and deformations introduced by the morphological operations applied during the segmentation of IR hand images.
4) *Slap segmentation*: Unlike the existing unsupervised component clustering, the proposed segmentation uses the approximate location of each labeled finger determined using simultaneously acquired IR hand dorsal image. It handles the problems in the existing clustering, such as halo, sweat, and poor quality fingerprints, and improper orientation for better segmentation. The location of each labeled finger in the slap image is stored as binary images. In order to extract the fingerprint corresponding to a labeled finger, only components belonging to that finger are considered and the topmost component amongst them is marked as the fingerprint. For better understanding, assume that the fingerprint corresponding to f_i finger needs to be determined from the slap image I and their location is stored in B_i. Since the fingerprint requires only the information provided by the areas belonging to f_i, all unnecessary areas are removed using
$$A_i(x, y) = B_i(x, y) \times I(x, y) \tag{3}$$
where A_i denotes the modified image containing the area belonging to f_i and (x, y) denotes the pixel location. Components are extracted from A_i and their centers are calculated using the component detection algorithm presented in [3]. The component with the minimum y-coordinate of center is the topmost component, i.e., the fingerprint corresponding to f_i. This is repeated to extract the fingerprint from each labeled finger. It is worth to mention that the proposed segmentation does not require hand detection and component clustering for fingerprint extraction and labeling because hand and labeled finger locations are already known after the IR hand segmentation.

An example of the proposed slap segmentation is shown in Fig. 4.

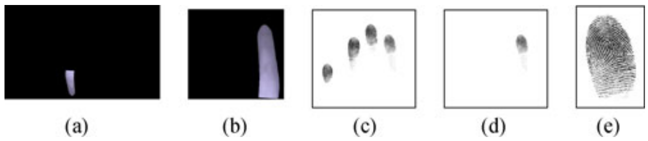


Fig. 4. Illustration of the slap image segmentation. These depict (a) ring finger location in Fig. 3(a); (b) mapped image B_i; (c) slap image I; (d) modified slap image A_i; and (e) extracted fingerprint.

C. Multibiometric Fusion

In this section, a multibiometric fusion has been proposed, which authenticates a user using either slap fingerprint matching or the fusion of palm dorsal veins and IR hand geometry. It computes slap fingerprint matching score using quality-based fusion. Subsequently serial fusion is applied where the fusion of palm dorsal veins and IR hand geometry is performed when the slap matching score is found unsuitable for authentication.

1) Slap Image Matching: Single fingerprints can be matched using minutiae matching, correlation matching, and ridge matching [15]. Minutiae-based fingerprint matchers outperform both correlation- and ridge-based fingerprint matchers when a global fingerprint structure is deformed by the elastic fingertip skin or a partial fingerprint is captured [16]. Since these are the usual phenomena in fingerprint, the proposed system utilizes minutiae-feature-based matching. Minutiae features are extracted from each labeled fingerprint of the slap image using MINDTCT and these are matched with the corresponding template stored in the database using Bozorth [17]. The fusion of the matching scores can avoid normalization because the fingerprint matching scores share similar behavior, i.e., they denote the same biometric trait (i.e., fingerprint), feature extraction, and matching algorithms [12]. The performance of an authentication system depends on the quality of involved biometric traits and fortunately the quality of fingerprints can be estimated accurately for fusion. Such a fusion is referred as quality-based fusion [12]. Quality-based fusion proposed in [18] has demonstrated better performance than other existing fusion rules for slap fingerprints, and hence, it is utilized for fusing the single fingerprints. It defines the fingerprint quality using symmetric filters, which aims to measure the uniformity in ridge–valley flow irrespective of the curvature. Mathematically, let q_i and m_i denote the quality and the matching score, respectively, corresponding to the ith fingerprint, where $i = 1$, 2, 3, or 4. Then, the resulting fused score referred as slap matching score s_s is given by

$$s_s = \frac{\sum_{i=1}^{4} q_i \times m_i}{\sum_{i=1}^{4} q_i}. \tag{4}$$

2) Serial Fusion: In the proposed serial fusion, the efficacy of slap matching score is analyzed by dividing the matching scores into the following three regions.

1) The region where the matching scores are sufficiently low to claim mismatch.
2) The region where accurate decision-making is not possible due to overlapping false accept rate (FAR) and false reject rate (FRR).
3) The region where the matching scores are suitably high to predict match.

The authentication errors may be introduced in the region having overlapping FAR and FRR. Such a region is also referred as an uncertainty region [8]. In contrast, other regions having nonoverlapping FAR and FRR performs accurate authentication. Assume that th_1 is the threshold used to separate the low matching score region and the uncertainty region while threshold th_2 separates the uncertainty region and the high matching score region. If the slap fingerprint matching score s_s is lower than th_1, then mismatch is indicated while the match is indicated when s_s is greater than th_2. Slap fingerprint matching is not effective in the remaining cases, i.e., s_s lies between th_1 and th_2. Mathematically, the decision, DECISION, is given by

$$\text{DECISION} = \begin{cases} \text{MISMATCH}, & \text{if } s_s < \text{th}_1 \\ \text{UNDECIDED}, & \text{if } \text{th}_1 \le s_s \le \text{th}_2 \\ \text{MATCH}, & \text{Otherwise} \end{cases}. \tag{5}$$

In this case, if DECISION is given by UNDECIDED, palm dorsal veins and IR hand geometry are required for authentication.

Veins are extracted from the palm dorsal area using multiscale matched filtering and subsequently they are matched using phase correlation matching to obtain the palm dorsal vein matching score [4]. Veins can also be matched by matching the minutiae features [19] but such a matching is erroneous because minutiae cannot be accurately localized in the palm dorsal veins [20] and only a small number of minutiae are present in the vein pattern [21]. Hence, minutiae matching is avoided for the palm dorsal matching. Similarly, finger length and width of all fingers are extracted and matched using PCA to obtain the IR hand geometry matching score [4]. Other hand geometry features such as shape features of full hand and palm dorsal are avoided for the consideration because it is shown in [4] that these features performed poorly due to the elastic deformations introduced by different opening and closing of fingers. Score normalization is required before the fusion of the matching scores of palm dorsal vein and IR hand geometry because they are derived from different biometric traits possessing different characteristics, feature extraction, and matching algorithms [12]. Thus, min–max normalization is applied to the matching scores prior to fusion. Moreover, in score-level fusion, each trait contributes to the fused score and the contribution decides the efficacy of the fusion. Better performance can be expected if the traits exhibiting better performance contribute more than the remaining traits. Usually, the performance of IR hand geometry is significantly low as compared to palm dorsal vein. Hence, the performance can be improved if IR hand geometry gives less importance to the fused score as compared to the palm dorsal vein. Motivated by this, the contribution of each trait is decided by their performance. Mathematically, assume that s_p and s_h are the normalized matching score of palm dorsal veins and IR hand geometry, respectively, whereas their performances are denoted by p_p and p_h, respectively. Then, the fused score s_f is given by

$$s_f = \frac{p_p \times s_p + p_h \times s_h}{p_p + p_h}. \tag{6}$$

The fused score s_f is used to take the decision, which can either match/mismatch in case of verification or identity of the user in case of identification.

IV. Experimental Results

The proposed system is the first of its kind in terms of fusion and simultaneous acquisition of these traits. Hence, no such database is publicly available. Therefore, a database is acquired for the experimentation under varying illumination conditions from 200 users who belong to an age group ranging from 25 to 45 years. The majority of the user population consists of security guards, gardeners, kitchen workers, electricians, and farmers. Most of them have poor quality fingerprints and to further create more challenging dataset, large temporal variations are introduced by acquiring the database into two different sessions with an average time gap of 20 days. The database contains simultaneously acquired slap images and IR hand images of both hands and each hand is treated as a different identity. Thus, total 400 hands are used for the evaluation. The size of each slap image is of 1600 $\times$ 1500 pixels, whereas that of an IR hand image is 1052 $\times$ 768 pixels. Each hand image is acquired two times in the first session, whereas three times in the second session. Hence, the database contains total 2000 slap images and 2000 IR hand images. Out of these, hand images acquired in the first and second sessions are used to create the probe and testing sets. The performance is assessed by matching the images acquired in separate sessions. Hence, total 2400 (1200 $\times$ 2) genuine matchings and 957 600 (1200 $\times$ 798) impostor matchings are present.

The performance is evaluated in verification using: first, the receiver operating characteristic (ROC) curve [22] that depicts the behavior of FRR and FAR; and second, the equal error rate (EER), which is given by FRR at a threshold where FAR and FRR are equal. For identification, the performance is assessed by correct recognition rate (CRR), which provides the accuracy of the top best match.

A. Parameter Tuning

The performance of the system depends on several parameters, which require proper tuning in the following ways.

1) Homography Matrix H: Knowledge transfer requires proper tuning of H, which transforms the finger locations in an IR hand image to the locations in a slap image. Both simultaneously acquired images (i.e., IR hand and slap image) analyze same slap platen area from different viewpoints, which introduces perspective transformation between the images that has eight degrees of freedom. Hence, at least four noncollinear points are required to uniquely estimate the homography matrix [23]. Since the position of slap platen in an IR image is fixed due to the acquisition setup, the four corner points of the slap platen are manually marked on one randomly selected image and utilized to estimate H using eight point algorithm [23]. The correspondence between manually marked points and slap image is shown in Fig. 5.

2) Serial Fusion: Determination of normalization function and performance of the recognition system for palm dorsal veins and IR hand geometry along with thresholds th_1 and th_2 play important role in the fusion technique. Assume that F and p denote the normalization function and performance of a recognition system, which use one modality. These parameters are estimated by analyzing the probe set, which contains two images per hand of that modality. The probe set is segmented into two parts, T_1 and T_2, in such a way that each part has exactly one image per hand. Samples in T_1 are matched with samples in T_2 to obtain the matching scores. These scores are used to obtain CRR, which gives the performance of the modality and it is set as p. The numerical values of performance for palm dorsal vein (p_p) and IR hand geometry (p_h) are 98.81 and 85.47, respectively. Further, F is given by

$$F(x) = \begin{cases} 0, & \text{if} \quad x < x_{\min} \\ \frac{x - x_{\min}}{x_{\max} - x_{\min}}, & \text{if} \quad x_{\min} \le x \le x_{\max} \\ 1, & \text{otherwise} \end{cases} \tag{7}$$

where $x_{\min}$ and $x_{\max}$ denote the minimum and maximum matching scores of the modality, respectively. Serial fusion is used if slap fingerprint matching score lies between th_1 and th_2, which are set to zero FRR and zero FAR, respectively, [24] of the evaluated matching score. The numerical values of th_1 and th_2 obtained from the experiments are 0.57 and 0.63, respectively.

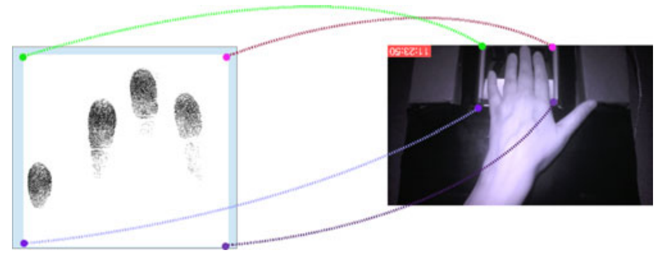


Fig. 5. Correspondence between manually marked points in an IR hand dorsal image and a slap image.

B. Usefulness of Knowledge Transfer

In this section, the performance of the proposed slap segmentation using knowledge transfer is compared with the best known state of the art systems [18] and [25]. The EER of [18], [25], and the proposed system is 2.97%, 2.64%, and 2.14%, respectively, whereas the corresponding CRRs are 97.53%, 97.68%, and 98.10%, respectively. The ROC curves of the systems are shown in Fig. 6(a). The proposed system performs better than systems [18] and [25] because the knowledge transfer from IR hand images provides the approximately correct information about finger locations and hand type (left/right) even if the slap image contains small area, sweat, and improper orientation. Some examples depicting the importance of knowledge transfer are shown in Fig. 7. It shows the erroneous components detected by systems [18] and [25] in green color, whereas the corresponding correct components detected by the proposed system are shown in red color.

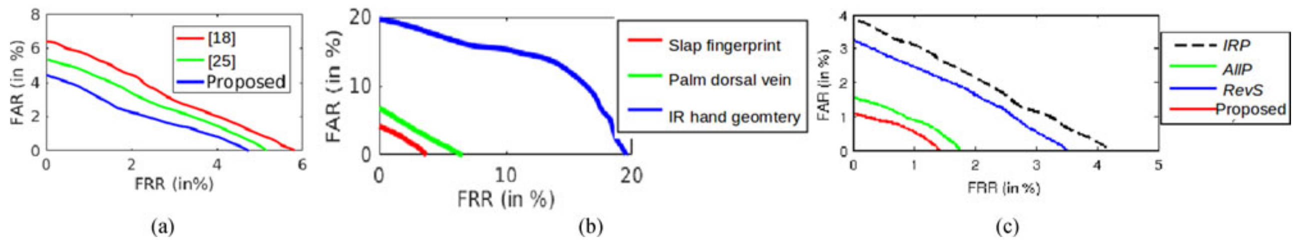


Fig. 6. ROC curves of (a) slap fingerprint systems, (b) single traits, and (c) systems after fusing several traits.

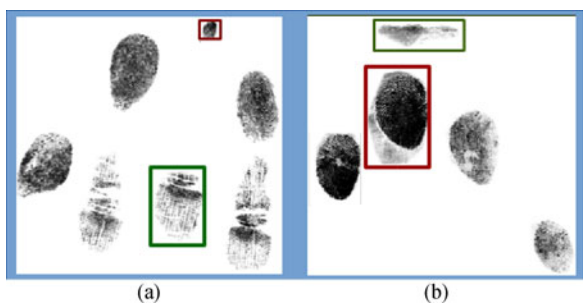


Fig. 7. Importance of knowledge transfer.

TABLE I
PERFORMANCE OF SINGLE TRAITS

Traits	EER	CRR
Slap fingerprint	2.14%	98.10%
Palm dorsal vein	3.23%	97.14%
IR Hand geometry	13.65%	83.33%

C. Performance of Single Traits

This section aims to analyze the performance of single traits. EER and CRR obtained by matching single traits are shown in Table I and the corresponding ROC curves are shown in Fig. 6(b). These indicate that the least performance is exhibited by IR hand geometry because hand geometry possesses low uniqueness. Moreover, palm dorsal veins demonstrate lower performance than slap fingerprints. It performs incorrectly when genuine veins are missed and/or spurious veins are generated due to hair, nonuniform illumination, and skin properties. The best performance is obtained by matching slap fingerprint because even a single fingerprint possesses high uniqueness [15] and fusion of several fingerprints further enhances the uniqueness.

D. Performance of Fusing Several Traits

The performance achieved by fusing several traits has been analyzed in this section. Three systems are designed using various fusion strategies for the evaluation viz., IRP, AllP, and RevS. In IRP, palm dorsal veins and IR hand geometry are fused using the while all the traits are fused in AllP. Both these parallel fusion systems utilize score-level fusion based on min–max normalization. In contrast, RevS uses serial fusion but the ordering of modalities is interchanged. That is, it first fuses palm dorsal veins and IR hand geometry for authentication followed by slap fingerprint, if required. EER and CRR of the fused systems are shown in Table II and their corresponding ROC curves are depicted in Fig. 6(c). The following can be observed.

TABLE II
PERFORMANCE AFTER FUSING SEVERAL TRAITS

Systems	Traits used	EER	CRR
IRP	Palm vein and Hand geometry	2.01%	98.45%
$AllP$	All	1.81%	98.92%
$RevS$	All	0.92%	100%
Proposed	All	0.72%	100%

1) Tables I and II indicate that better performance can be achieved when multiple traits are fused. Small performance improvement can be seen even by fusing of IR hand geometry with palm dorsal veins (refer IRP). However, this is not always the case and a proper fusion strategy plays a crucial role in multibiometric systems. We have fused all the traits using decision-level fusion based on majority voting, but it is observed that even slap fingerprint and palm dorsal vein systems outperform such a fused system. The EER and CRR obtained by applying the decision-level fusion are 9.36% and 89.91%, respectively. The poor performance can be attributed to the low performance of IR hand geometry. Moreover, feature-level fusion is avoided in the fusion because it is useful when the traits utilized in the fusion are closely related to each other, but we have utilized all independent traits.
2) Serial-fusion-based systems (i.e., RevS and proposed) perform better than parallel-fusion-based system (i.e., IRP and AllP) because in some cases either slap fingerprint matching or the fusion of palm dorsal veins and IR hand geometry is sufficient for accurate matching. When all the modalities are fused, the confidence of one modality can be decreased when the other modalities are of poor quality [24].
3) RevS and the proposed system identify all users correctly, i.e., CRR is 100%. Moreover, they are significantly better in terms of computational time as compared to the other systems because they avoid the matching of unnecessary modalities. The proposed system avoids the matching of palm dorsal veins and IR hand geometry in approximately 95% of the cases, whereas RevS avoids slap fingerprint matching in approximately 94% of the cases. Since palm dorsal veins matching, which needs moderately higher computational time than the slap fingerprint matching, RevS requires more time computations than the proposed system. Moreover, the proposed system exhibits better performance than RevS in terms of EER.

V. Conclusion

This paper proposed a multibiometric system that uses slap fingerprints, palm dorsal vein, and hand geometry for accurate person authentication. An acquisition setup, which can simultaneously acquire slap images and IR hand dorsal images, was designed to acquire images. An IR hand dorsal image was segmented into palm dorsal area and fingers. Palm dorsal vein was extracted from palm dorsal area, whereas the length and width of the labeled fingers were used to define the IR hand geometry. A slap segmentation was proposed to extract the single fingerprints present in a hand. It relied on the knowledge of the approximate location of the fingers and hand type (either left or right) present in the slap image. This knowledge was provided simultaneously by the acquired IR hand dorsal image. The matching scores generated by matching the slap fingerprints, palm dorsal vein, and IR hand geometry were fused for authentication.

Experimental results demonstrated that better slap authentication can be performed by incorporating the knowledge provided by the simultaneously acquired IR hand images. Moreover, it indicated that better performance can be achieved when all traits are fused using the proposed serial fusion. Further, it can be observed that the all traits are simultaneously acquired using the proposed acquisition setup. Due to this, the setup incurs low acquisition time and thereby offers good user acceptability. Machine learning approaches for features matching may be explored to look for better authentication of vein patterns and IR hand geometry.

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