出國報告(出國類別:學術研討會)

赴日本參加
MVA 2015 - 14th IAPR International Conference on Machine Vision Applications
返國報告

服 務 機 關 ：海軍軍官學校
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摘要

計畫主持人於 2015 年 5 月 18 日研討會當日赴桃園機場坐一早班機飛往日本成田機場，並於下午四點抵達本次國際研討會開會東京的科學未來館(National Museum of Emerging Science and Innovation)進行報到和註冊，並領取大會資料和議程相關資料。5 月 21 日上午發表論文，題目為 Dorsal Hand Vein Recognition based on EP-Tree。主要內容是報告手背靜脈識別是新興的身份認證技術。手背靜脈識別是以手背靜脈骨架特徵進行識別，如何準確地擷取手背靜脈的骨架特徵，是該研究計畫的重點。本計畫重點研究了手背靜脈骨架特徵提取演算法。將靜脈影像骨架化後，擷取出可識別的特徵點(Feature points)及對應的特徵距離(Feature distance)視為有效特徵，並提出模式樹(Pattern tree)的搜尋方式快速找尋出相似的靜脈影像，最後運用最小距離分類器進行精確識別；實驗中亦採用傳統的分割細化法、沉浸分水嶺等演算法等進行比較分析，本研究計畫提出的創新方法，不但具即時性且能夠精確地的達到辨識個人身份鑑識的功能。報告後多人發問與發表建言，討論熱烈。

會議期間，主持人亦與一些研究學者討論資訊安全、生物認證以及影像處理在產業上應用的知識與技術。

目次

出席國際會議心得報告

一、目的：

出席國際大型研討會，可與國際著名學者討論與交流有關資訊安全及數位影像處理在不同領域下的應用，並發表個人論文，參與討論以增加個人於本研究領域廣度及深度。

二、會議概況：

國際機器視覺應用研討會（MVA）為每兩年舉辦一次的國際學術研討會，今年為第 14 屆於 2015 年 5 月 18 日至 5 月 22 日在日本東京的科學未來館(National Museum of Emerging Science and Innovation)舉行，這是國際模式識別協會(IAPR)每年所舉辦的其中一場關於機器視覺、電子電機以及計算機頗具盛名的國際研討會，依照慣例，均在日本舉辦，今年由日本產業技術綜合研究機構(National Institute of Advanced Industrial Science and Technology)主辦。本次研討內容偏重計算機視覺、3D 影像重建以及影像處理領域等相關研究技術探討。會議邀請了許多重量級的學者與會演講，參加的學者以亞洲及歐美洲地區為最多數，每場演講後的討論正是各個學者意見互相交流的時間，可以相互激發思慮。本次研討會學術交流分為三個部份，包括：(一)專題演講(keynote speakers)、(二)口頭報告(presentations)以及(三)海報發表(posters)。大會安排於 5 月 19 日及 21 日每天一場的專題演講、10~15 篇的口頭報告，以及 40 篇左右的海報發表。本次研討會共計錄取 154 篇論文，其中 36 篇口頭報告，而其餘 118 篇為海報發表。本次大會五天共排進 9 個議程，每一個議程平均 3~5 場的報告；本人此次發表的研討會論文在眾多接受的論文中，有幸榮獲大會選為口頭報告 (接受率 23%) ，並於 21 日上午於生物醫學影像議程中發表。由於專題演講、口頭發表與海報論文發表乃分開時段進行，三天下來，研討會之論文發表均可每場次參加，且與國外學者共同討論研究心得獲益良多。此外本次會議議程相當緊湊，除了白天的論文發表外，每晚均安排文化響宴。連續三天

早出晚歸，相當辛苦，不過也過得相當充實。除在學術專業與各國學者交流外，對異國風情文化亦略有體會與感受。

三、過程與心得：

計畫主持人參與會議經過，如下所述：

主持人於 2015 年 5 月 18 日研討會當日赴桃園機場坐一早班機飛往日本成田機場，並於下午四點抵達本次國際研討會開會東京的科學未來館(National Museum of Emerging Science and Innovation)進行報到和註冊，並領取大會資料和議程相關資料。此次大會的主要學術議程有邀請演講、口頭報告與海報發表等三種方式。主持人於會議期間 5 月 21 日早上 11 點 10 分發表一篇口頭論文報告，題目為" Dorsal Hand Vein Recognition based on EP-Tree "。主要內容是報告手背靜脈識別是新興的身份認證技術。手背靜脈識別是以手背靜脈骨架特徵進行識別，如何準確地擷取手背靜脈的骨架特徵，是該研究計畫的重點。本計畫重點研究了手背靜脈骨架特徵提取演算法。將靜脈影像骨架化後，擷取出可識別的特徵點(Feature points)及對應的特徵距離(Feature distance)視為有效特徵，並提出模式樹(Pattern tree)的搜尋方式快速找尋出相似的靜脈影像，最後運用最小距離分類器進行精確識別；實驗中亦採用傳統的分割細化法、沉浸分水嶺等演算法等進行比較分析，本研究計畫提出的創新方法，不但具即時性且能夠精確地的達到辨識個人身份鑑識的功能。報告後多人發問與發表建言，討論熱烈。其中有學者對於論文提問有關影像來源及窒礙難行處理情形的解決方案；另有學者則是詢問論文的實驗設計以及與結果的比對驗證。顯示此一領域的國際學者在研究上是理論與實驗技術並重的。另外本次研討會的海報展示，展出共計 118 篇：模式識別、影像處理、3D 影像重建、機器視覺等各方面都有，並有各個論文作者分別在現場說明。

此外，大會另一項重點乃是大會於 19 日至 21 日每日均安排了一場專題演講，其中包含了捷克科技大學的 Tomas Pajdla 教授介紹及展示運用照片實施三維影像重建技術原理及運用，最後可以運用於地理資訊系統。而他的研究領域包含了研發各種較先進的機

器人視覺系統，另在會議現場亦展示了相關二維影像結合一些資訊轉換成 3D 立體影像，課題相當重要且有趣；日本名古屋大學的 Johji Tajima 教授發表了從身體、心理以及生物學觀點來看彩色影像處理，說明許多領域的科學幾乎都運用到彩色影像處理，然而由於不熟悉導致不正確的運用，演講內容則是以身體與心理的觀點來評估物體彩色影像的亮度，並運用標準彩色影像資料庫(SOCS)驗證，其目的就是為了讓不同領域的研究者對彩色影像處理有基本的認識。此外，本次會議亦邀請美國康乃爾大學的 Ramin Zabih 教授介紹了近期醫學影像的研究技術，說明醫學影像已不同於以往的研究重點僅止於註冊(Registration)及分割(Segmentation)，而現在的醫學影像乃著重的重點在處理高解析度的 CT 以 MR 影像，而移動模糊(Motion blurring)乃是這類型影像所需解決的關鍵問題，Ramin Zabih 教授在演講時發表了他與他的團隊針對醫學影像處理的許多不同解決方法；讓我們與會者受益良多。這場研討會所邀請之專家學者演講之主題幾乎都與影像視覺以及影像處理有濃厚的關係，而與本人未來的研究相當有關連，參加本次研討會，雖然只有短短三天，但所學習的新知，卻是需要花費大量研讀時間才可獲得的，因此也激發了個人在相關研究上的靈感。

另本次研討會亦邀請了相關業界代表展示相關軟硬體成品，我也利用會議中場休息時間，參觀了一些研究成果，其中我對日本機器人留下相當深刻的印象，日本從最原始應用於工業界的機械手臂，到目前積極研發能移動的機器人，這對人類的生活影響甚鉅，一旦機器人能平衡來替人類工作，則其應用將十分廣泛，例如處理繁瑣的家務，或者用來從事高危險或人力密集度高的產業，也正因為商機無線，所以世界各國願意投入大筆資金從事這方面的研究，此次利用研討會場合也與所謂的日本機器人做了一些互動，其做工之細緻以及機器人的反應，實在讓我嘆為觀止，反觀我國的研究能量，若積極實施此方面的研究，其研發實力應不會輸給日本才是。研討會最後一天(5 月 22 日)議程為安排市區旅遊，無相關論文發表以及學術議程，因此本人並無參加，中午過後隨即搭機返台，結束本次受益良多的研討會。

四、論文發表：

Dorsal Hand Vein Recognition based on EP-Tree

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KEYWORDS:

Main subjects: Security

Proposed method(s): End-points-tree (EP-tree)

Keywords: Dorsal hand vein recognition; Minutiae features; End points tree; Biometrics

ABSTRACT:

Vein recognition is emerging as a popular approach to biometric recognition. This study sought to represent the shape of veins by analyzing variations in the local features obtained in images of veins. In the proposed framework, minutiae features are extracted from dorsal hand vein patterns for recognition. These include end points and the distance between the two end points as measured along the boundary of the image. In addition, we proposed an end-points-tree (EP-tree) to accelerate matching performance and evaluate the discriminatory power of these feature points for the purposes of verifying one's identity. We employed a total of 5,544 images of dorsal hand veins from 308 individuals in order to validate the proposed recognition method. In a comparison with six existing verification algorithms, the proposed method achieves the highest accuracy in the lowest matching time. Our results demonstrate the effectiveness of the proposed method as a promising approach to vein recognition.

論文中文摘要：

基於 ER 樹之手背靜脈識別之研究

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手背靜脈識別是新興的身份認證技術。手背靜脈識別是以手背靜脈骨架特徵進行識別，如何準確地擷取手背靜脈的骨架特徵，是該研究計畫的重點。本計畫重點研究了手背靜脈骨架特徵提取演算法。將靜脈影像骨架化後，擷取出可識別的特徵點(Feature points)及對應的特徵距離(Feature distance)視為有效特徵，並提出模式樹(Pattern tree)的搜尋方式快速找尋出相似的靜脈影像，最後運用最小距離分類器進行精確識別；實驗中亦採用傳統的分割細化法、沉浸分水嶺等演算法等進行比較分析，本研究計畫提出的創新方法，不但具即時性且能夠精確地的達到辨識個人身份鑑識的功能。

Dorsal Hand Vein Recognition based on EP-Tree

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Abstract

Vein recognition, as an emerging biometric recognition approach, is becoming a very active topic in both research and practical applications. In our framework, the minutiae features is extracted from the dorsal hand vein patterns for recognition, which include end points and the distance between the two end points as measured along the boundary of the image. In addition, the end-points-tree (EP-tree) is proposed to accelerate the matching performance and evaluate the discriminating power of these end points for person verification purposes. We employed a total of 4,280 images of dorsal hand veins from 214 individuals in order to validate the proposed recognition method. In a comparison with three existing verification algorithms, the proposed method achieves the highest accuracy in the lowest matching time.

1. Introduction

Biometrics-based identity verification technologies are based on the distinctive information in human biometric traits including facial images, hand vein outlines, fingerprints, palmprints, retinal information, handwriting, signature, and gait [1]. Among them, vein recognition is tested as the most accurate manner of personal identification [2]. Therefore, nowadays many automatic security systems based on vein recognition have been deployed worldwide for border control, restricted access, and so on.

In general, dorsal hand vein images consist of many different features such as the geometric pattern, principal line, and minutiae. All these desirable properties (i.e., uniqueness, stability and non-invasiveness) make vein recognition suitable for highly reliable personal identification. Hsu et al. [3] successfully used modified 2-directional 2-dimensional principal component analysis ($(2D)^2$PCA) to obtain eigenveins, which is a low dimensional representation of vein pattern features. Lin et al. [4] proposed the use of multiple multi-resolution analysis features for analyzing palm-dorsal vein patterns. Lee [5] proposed an innovative, robust directional 2-D Gabor filters technique for the encoding of vein features in bit string representation. The fusion of multiple features [4-5] may improve recognition accuracy, but such approaches are time consuming. Geometry-based approaches [6-8] extract local features such as the locations and local statistics of the principal veins and minutiae points. Wang et al. [6] employed the minutiae features extracted from the vein patterns for recognition, which include bifurcation and ending points. These minutiae features are used as a geometric representation of the shape of vein patterns. Kumar et al. [7] presented a new approach to authenticate individuals using triangulation of hand vein images and simultaneous to extract the knuckle shape information. The resulting rotation and translation invariant feature vector is variable in length as determined by the number of identified triplets. Lee et al. [8] employed minutia-based alignment and local binary pattern for finger vein recognition. However, above the geometry-based methods are difficult to extract, represent, and compare, and it is time consuming to measure the similarity between the minutiae points.

In this paper, a new feature extraction approach for vein patterns is based on minutiae points where the positions of end-points from the skeletal representation of vein patterns are being used. The main contributions of this paper can be summarized as follows.

(1) Based on the minutiae points of vein images, we extracted end-point features and the boundary distances between the two end points along the boundary of every sub-image. The novel method of feature extraction offers the features compression of vein images and shows the vein characteristic properly. Further details of this strategy can be seen Section 3.

(2) To reduce matching cost, the end-point-tree (EP-tree) is proposed to search the similar vein image in the dorsal hand vein database. Therefore, we only match the similar images to further improve the computing time for vein recognition.

The rest of this paper is organized as follows. Section 2 briefly introduces the preprocessing of vein images. A detailed description of the proposed dorsal hand vein recognition method is given in Section 3. Experimental results are presented and discussed in Section 4, and conclusions are given in Section 5.

2. Vein Image Preprocessing

To ensure that the proper vein features can be extracted from the dorsal hand vein image, it is essential to preprocess the images. The dorsal vein hand database presented in this study is reported in [3]. The features of vein patterns extracted from the same region in different dorsal hand vein images are compared for verification. The extracted region is known as the region of interest (ROI). The ROI fixing process has a significant influence on the accuracy of verification. The preprocessing procedure employed in this study is comprehensively described in [3]. In addition, enhancing the performance of vein recognition requires the extraction of texture from the veins in the image background. In this paper, a global/local threshold algorithm [9] was used to segment the vein patterns from the background. The binary image in Fig. 1(b) illustrates the vein pattern has been successfully segmented from the original image after applying the global and local threshold algorithm.

Extracting the end points from the vein structures requires computational thinning of the vein patterns using mathematical morphology operators. This paper performed the thinning operation on vein binary image using the well-known Stentiford thinning algorithm [10]; however, even this was insufficient to satisfactorily reveal the structures associated with the vein patterns. This can be attributed to fact that the resulting binary pattern also contains redundant branches; i.e., isolated regions with negligible connectivity. Figure 1(c) presents the skeleton of the vein patterns extracted using the thinning algorithm. The most common approaches to overcome redundant branches are based on skeleton pruning methods. By using skeleton pruning algorithm [11] spurious segments induced by isolated regions with small connectivity are eliminated whilst the dominant veins are retained, as shown in Fig. 1(d). It can be seen that after the pruning process, the structures associated with the vein patterns have been effectively extracted while the shape of the vein pattern remains well preserved.

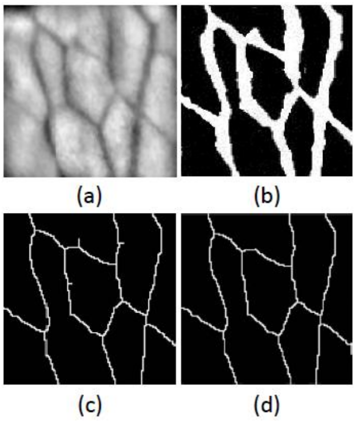

Figure 1. Skeleton of the vein pattern: (a) original ROI image, (b) binary image of vein pattern, (c) skeleton of pattern after thinning algorithm, and (d) vein structures extracted following pruning process.

3. Proposed Method

The proposed method presented in this paper for the recognition of dorsal hand veins involves two basic processes: feature extraction and matching. The procedures of two novel algorithms are stated as follows:

3.1. Extraction of minutiae features

Based on minutiae features, the vein pattern can be well represented using a number of end points in the dorsal hand vein image. Obtaining the end points from the skeleton of vein patterns involves partitioning the thinned image into four sub-images with different image dimensions (128×128, 96×96, 64×64, and 32×32 pixels), as shown in Fig. 2. In each of the sub-images, the end points represent intersections of image boundaries and veins. The proposed method makes it possible to determine the number of end points and the distance between two end points along the boundary. However, in each sub-image, the number of end points and the distances along the boundaries are selected as main features with which to represent the vein properties. According to the above discussion, the entire feature extraction framework is given as follows:

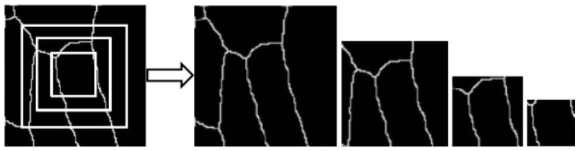

Figure 2. Inward partitioning of thinned image resulting in four sub-images of various dimensions (128×128, 96×96, 64×64, and 32×32 pixels)

(1) Vein images are partitioned into different dimensions. The sub-vein images are extracted from thinning image according to the size extract-window (128×128, 96×96, 64×64, and 32×32 pixels), respectively.

(2) The points at which the veins meet the four boundaries in each sub-image are extracted, and then the numbers of boundaries associated with each end point are calculated. The number of end points along the boundaries of the sub-image in Fig. 3 are 3, 1, 3, and 1 (clockwise from the top), respectively.

(3) The distances between two end points and between end points and vertices are then calculated. For example, the Fig. 3 shows

the boundary distances as $L_1, L_2, \cdots, L_{12}$, respectively.

(4) Every sub-vein image can be found two feature sets based on the end points and boundary distances.

- The first feature vector is extracted using end points, and resulting in $p1, p2, p3, p4, q1, q2, q3, q4, r1, r2, r3, r4, s1, s2, s3, s4$, respectively. $p1 \sim p4$ are the number of end points associated with the four boundaries in the 128×128 pixel sub-image. Thus, $q1 \sim q4$, $r1 \sim r4$, and $s1 \sim s4$ are the number of end points along the four boundaries in the sub-other images (96×96 , 64×64 , and 32×32 pixels), respectively.
- The second feature vector is selected according to the boundary distances, as $i_1, i_2, \cdots, i_n, j_1, j_2, \cdots, j_m, k_1, k_2, \cdots, k_k, l_1, l_2, \cdots, l_x$, respectively. $i_1, i_2, \cdots, i_n$ are the distances along the boundaries of the 128×128 pixel sub-image. $j_1, j_2, \cdots, j_m$, $k_1, k_2, \cdots, k_k$, and $l_1, l_2, \cdots, l_x$ are the boundary distances of the other three images, 96×96 , 64×64 , and 32×32 pixels, respectively.

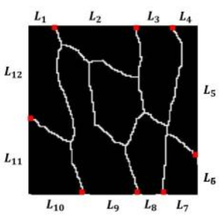

Figure 3. Extraction of end points and boundary distances from the skeleton of vein patterns.

The proposed method makes it possible to precisely determine the end points (feature points) and boundary distances (feature distances), such that the features present an accurate representation of the vein image. The method used for feature extraction does not involve searching the entire image, but only searching information related to the boundaries of images. Thus, the proposed method extracts the vein features precisely while reducing computational costs.

3.2. Matching of feature vectors

This paper proposes a novel matching algorithm which requires a comparison of similar feature vectors only. This reduces the computation time and increases recognition efficiency. The proposed matching method progresses along the following steps:

(1) Each level of the proposed EP-tree structure (based on the first feature vector) is defined by the number of end points of various dimensions. As a result, the four dimensions of the vein images are reflected in the four levels of the EP-tree.

(2) Using the EP-tree, every vein image can be rapidly matched to similar patterns. The description of the EP-tree (shown in Fig. 4) is as follows:

- The first level involves the quantity set of end points along the four boundaries in each sub-image of 128×128 pixels. We therefore assume that there are n vein images with the first sample $\{p1^1, p1^2, p1^3, p1^4\}$ and the last sample $\{pn^1, pn^2, pn^3, pn^4\}$.
- The second level is the quantity set of ends point along the four boundaries of each sub-image of 96×96 pixels. In the second level of the EP-tree, we assume that m vein images belong to the $p1$ class, the last sample is

$\{qm^1, qm^2, qm^3, qm^4\}$, and p vein images belong to the $p2$ class, such that the last sample is $\{qp^1, qp^2, qp^3, qp^4\}$.

- The third level is the quantity set of end points along the four boundries of each sub-image of 64×64 pixels. In the third level of EP-tree, we assume that h vein images belong to the $p1$ and $q1$ class such that the last sample is $\{rh^1, rh^2, rh^3, rh^4\}$, and x vein images belong to the $p2$ and $q1$ class such that the last sample is $\{rx^1, rx^2, rx^3, rx^4\}$.
- The fourth level is the quantity set of end points along the four boundries of each sub-image of 32×32 pixels. In the fourth level of EP-tree, we assume that l vein images belong to the pn, q1 and rz class such that the last sample is $\{sl^1, sl^2, sl^3, sl^4\}$.

(3) Using the EP-tree, a test vein image is first matched to a group of similar images; i.e., different images may have the same number of end points along the four boundaries.

The fact that group is not unique makes it necessary to use the second feature vector (boundary distances) to obtain accurate matches. EP-tree makes it possible to match a test vein image to similar vein image groups. However, the second feature vector of group has feature dimensions the same as the distances along the boundaries. Therefore, we determined the similarity between two feature vectors (based on boundary distance) using three different measurements : the Cosine and Euclidean distances, and the Hamming distance (HD). However, the HD refers to similarity between binary feature vectors. Thus, when using the HD, real-valued vein feature vectors were normalized between 1 and -1, and quantized as follows:

$$Q(f_i) = \begin{cases} 1, & f_i \geq 0 \\ 0, & f_i < 0 \end{cases}, \quad i = 1, 2, \cdots, n \qquad (1)$$

in which each element of the real-valued feature vector f_i becomes 0 or 1, depending on its sign, where f_i represents a i th real-valued element of a feature vector extracted from the distance between veins along a boundary.

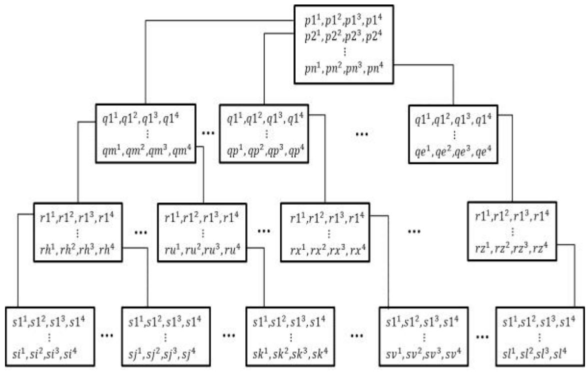

Figure 4. Structure of EP-tree

4. Experiment Results

The dorsal vein hand database employed in this study is reported in [5]. It includes 4,280 images from 214 volunteers (hence 214 different classes) with twenty images captured from each class. For each dorsal hand vein class, we selected eight samples from images taken in the first stage for training with all samples captured in other stages serving as test samples. A series of experiments was performed to evaluate the performance of the proposed method in identifying individuals based on a sequence of dorsal hand vein images.

The paper employed modern statistical methods to evaluate the performance of the biometric algorithms. Experiments were conducted in two modes: identification (i.e., one-to-many matching) and verification (i.e., one-to-one matching). In identification mode, the performance of the algorithm could be evaluated according to its correct recognition rate (CRR), which is the ratio of samples correctly classified to the total number of test samples. In verification mode, we adopted the well-known statistical pair, false acceptance rate (FAR) and false rejection rate (FRR) to evaluate the effectiveness of the proposed method. All experiments were executed using Matlab R2010a on a computer system of PIV 2.67GHz with 1GB RAM. The following subsections detail the experiments and results.

Table 1 Recognition results using four different methods

Methods	CRR (%)	EER (%)
Lin et al. [4]	98.31	1.77
Wang et al. [6]	93.87	5.88
Kumar et al. [7]	95.64	4.19
Proposed	99.64	0.74

Experiment results demonstrate the effectiveness of the proposed method in the extraction of features from images of dorsal hand veins, with a CRR of 99.64% using the vein database. In this database [5], Cosine distance yielded the best performance, whereas the HD presented the worst performance. We then ascertained the effectiveness and robustness of the proposed approach with regard to identification and compared the results obtained using the algorithms proposed by Wang et al. [6] and Kumar et al. [7], due to the fact that this is currently the most popular algorithms based on minutiae points. We also compared the proposed algorithm with the method based on multi-resolution descriptors [4]. To further evaluate the effectiveness of the proposed method, we performed a detailed comparison of the proposed method with the above methods using the dorsal hand vein database [5]. Table 1 outlines our experiment results. It shows the CRR of the four algorithms using the dorsal hand vein database. According to the results in Table1, the proposed method provided the best performance, followed in order by [4] (Lin et al.), [7] (Kumar et al.), and [6] (Wang et al.). In Table 1, we also see that the proposed method produces better results than the other methods, thanks to its ability to characterize minutiae descriptors of the dorsal hand veins. The proposed representation also reduces the matching time required by the EP-tree, which makes our method superior to that of existing methods.

5. Conclusion

This paper describes an efficient method to verify the identity of individuals from dorsal hand vein image. The minutiae features extracted include end points and the distance between them along boundaries of the images used. In addition, we proposed an EP-tree to accelerate matching performance and evaluate the discriminatory power of these feature points to facilitate the verification of identity. Our experiment results demonstrate the effectiveness of the proposed method. We also conducted a detailed comparison of performance with existing methods. Such comparisons and analysis are helpful in the further improvement of the performance of vein recognition methods.

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五、建議事項：

本次研討會給我的感覺是學術交流與國際視野開拓的重要性。國際間，針對各種專業領域不乏會有知名學者。在交流的過程中，可從問答之間，感受高手過招之樂；亦可在私下討論時，了解每位學者間所關注的焦點，能使我們對整體研究趨勢有些了解，有助我們掌握新的研究方向。因此，教育部或科技部往後應盡量補助國內年輕學者或博士生，早日參與國際學術會議，開拓其國際視野並邁向國際；同時，也希望能多多補助支持國內大專院校，承辦一些大型國際會議，使無法獲得出國補助的學生及國內年輕老師，也能參與國際會議，增加與國外學者進行交流與見習的機會，亦可提升台灣在國際上的知名度。總結此次學術之旅，共可歸結出幾點重要結論與建議：

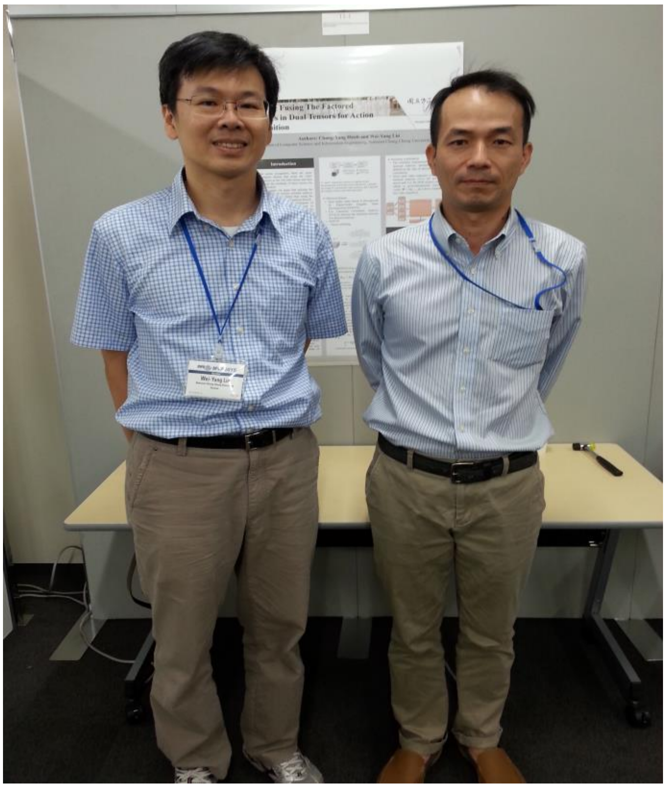
(1)每參與一次會議就有一次的體認與感觸，此次會議即已警覺近年來日韓等國一些資訊科技研究多為先進技術的理論問題。這顯示了尖端技術的發展，還是要有透徹的理論基礎，這或許是我們國家必須反思的課題。

(2)不少論文乃頗有前瞻性的議題，例如醫學影像的運用；工業上新型機器人設計等研究；甚有參考價值。但範圍頗廣，個人收穫者有限，台灣近年來學界亦逐漸重視此領域，希望能夠及時追趕國際腳步，使台灣的資訊科技在國際上一直走在最前端。

(3)建議政府針對有潛力以及具未來性的研究議題能擇項支援，不但可嘉惠師生，又可領先世界。另日本政府補助當地教授級教師與會與國際研究學者的交流，可作為國內借境。

附錄一：活動照片

本人於 MVA 2015 研討會會場註冊



本人於研討會會場與中正大學林維暘教授合影

附錄二：大會議程截錄

Thursday, May 21, 2015

Session 11: Action

Session 12: Biomedical