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A Keypoint Filtering Method for SIFT-based Palm-Vein Recognition

Kaveen Perera
Department of Computer and Information Sciences
Northumbria University at Newcastle
Newcastle Upon Tyne, United Kingdom
kaveen.perera@northumbria.ac.uk

Fouad Khelifi
Department of Computer and Information Sciences
Northumbria University at Newcastle
Newcastle Upon Tyne, United Kingdom
fouad.khelifi@northumbria.ac.uk

Ammar Belatreche
Department of Computer and Information Sciences
Northumbria University at Newcastle
Newcastle Upon Tyne, United Kingdom
ammar.belatreche@northumbria.ac.uk

Abstract— **A key issue with palm vein images is that slight movements of fingers and the thumb or changes in the hand pose can stretch the skin in different areas and alter the vein patterns. This can produce palm vein images with an infinite number of variations for a given subject. This paper presents a novel filtering method for SIFT-based feature matching referred to as the Mean and Median Distance (MMD) Filter, which checks the difference of keypoint coordinates and calculates the mean and the median in each direction in order to filter out the incorrect matches. Experiments conducted on the 850nm subset of the CASIA dataset show that the proposed MMD filter can maintain correct points and reduce false positives that were detected by other filtering methods. Comparison against existing SIFT-based palm vein recognition systems demonstrates that the proposed MMD filter produces excellent performance recording lower Equal Error Rate (EER) values.**

Keywords—MMD filter, SIFT descriptor matching, SIFT filtering, Palm Vein recognition

I. INTRODUCTION

The field of Biometrics has grown significantly over the last decade due to increasing worldwide demands and challenges in contactless digital security. Biometric traits are characterized by unique features and patterns that can be used to identify and recognize individuals and provide much more security over traditional authentication methods such as passwords or pin codes [1]. Palm vein biometrics recognition systems use the vein networks under the palm skin to establish a person's identity. Every human has their unique vein network pattern which does not subject to significant changes as they age. Hence, vascular biometrics is recognized to be more secure and reliable, and they provide greater details on their texture.

Palm vein recognition systems are contactless, hygienic, non-invasive, and user-friendly which enhances their user acceptance [2]. The deoxidized veins under the skin surface absorb Near-Infrared (NIR) light that penetrates the skin and appear darker. However, palm vein images have poor contrast and appear to be blurry as the skin scatters the NIR light radiance. These low contrast images are further degraded with image sensor noise, making the processing and feature extraction very challenging. Therefore, an appropriate contrast enhancement should be applied prior to feature extraction. Another key issue with palm vein images is that slight changes in the hand pose such as moving a finger, the thumb, or stretching the skin can alter the vein patterns. This can produce an infinite number of variations in palm vein images of the same person.

In [3], a contrast enhancement method has been proposed to address the issues associated with current image enhancement techniques used with palm vein recognition. This method is referred to as Multiple Overlapping Tiles (MOT). The performance of the MOT method has been tested on existing palm vein recognition systems with Scale Invariant Feature Transform (SIFT) and RootSIFT features. SIFT can be used to detect distinctive features on images. SIFT computes a feature descriptor which can then be used to match features between two images and find matching keypoint pairs. These features are tolerant to scale, translation, or rotation changes between two images.

This research used the MOT method to enhance image contrast and examined SIFT feature matching using Euclidian Distance (ED) [4], k-nearest neighbour (KNN) [5] matching methods, and Lowe's distance ratio test (RT) [6]. However, given the similarity of palm features, these methods still preserve a significant number of false positive matches.

To remove these false positives and enhance the performance of palm vein recognition, this research presents a novel filter which considers the mean and median distances between the horizontal and vertical distances of the geometric locations of matched keypoints, then use a set of rules to determine false positives. This filter is referred to as the Mean and Median Distance (MMD) filter. The experiment results has been compared with existing palm vein recognition systems based on SIFT [3], [7]–[10]. In section III the pseudo-code of the proposed MMD filter is presented. In section III *Fig. 1,* a workflow diagram of the proposed method is presented.

The remainder of the paper is structured as follows. A review of existing work is presented in Section II. The proposed method and experimental results have been discussed in section III and section IV, respectively. Section V contains the conclusions as well as recommendations for further developments.

II. RELATED WORK

Zhou and Kumar [11] introduced two line-based methods for palm vein recognition: Local Radon Transform (LRT) and Hessian Matrix-based feature extraction based methods. To start with, the contrast was enhanced by subtracting the estimated background intensity from the input image and applying Histogram Equalization. The features were extracted using Local Randon Transform (LRT) and matched using hamming distance. Then local dominant curvature was extracted from palm vein images using Hessian Matrix, which calculates the magnitudes from second order derivative eigenvalues of a palm vein image. LRT is encoded with six orientations. Hence, it is tolerant to translation variations. However, the Hessian matrix-based method produces

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redundancy in the feature vector and does not utilize all the information from training samples. Furthermore, it performs poorly when the images are blurry or unclear, which is an intrinsic problem with palm vein images.

Zhang and Hu [12] replicated the concept of minutiae points from fingerprint recognition into palm vein recognition. Using a database of 180 images, they report an EER of 1.82%. However, the structures of palm veins are more irregular to fingerprints and are very sensitive to small changes in the hand pose, making minutiae points not suitable to use with medium to large databases.

Lee [13] used a modified form of two directional two-dimensional linear discriminant analysis ($(2D)^2$LDA) to extract features from palm vein images. The background intensity has been subtracted from the input image to enhance the contrast and a median filter has been used to reduce noise. However, this method produces a smaller feature vector and requires 10 images for training per subject to achieve a higher accuracy.

Wu et al. [14] based their method on wavelet transform and Partial Least Square (PLS) using a database of 300 images captured from 50 subjects. PLS is prone to small sample sizes, which they have addressed using wavelet decomposition. They obtained a correct recognition rate of 99.86% using level 3 decomposition of Haar wavelets. However, their database is relatively small, and they do not present the EER values, which is critical to compare their performance with other palm vein recognition systems.

Wang et al. [15] proposed a Gabor wavelet-based method for palm vein recognition. They start with using Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement. The palm prints were removed using a low pass filter, followed by segmentation and thinning. Then correlation coefficient and features required for classification were extracted using Eigenvectors. They report higher performance than Local Projection Pattern (LPP), Principal Component Analysis (PCA), and minutiae features. However, they have used a small database of 178 images for their experiments which is not sufficient to establish the performance measurement of a palm vein recognition technique. Further, vital information is discarded during pre-processing by thinning and segmentation.

Fischer et al. [16] proposed a method referred to as Enhanced Local Gabor Binary Patterns Histogram Sequence (ELGBPHS). They applied Gabor filters in various scales and orientations, and features were extracted using Local Binary Pattern (LBP). They subdivide the image into smaller tiles to calculate histograms which is then used for matching using histogram interaction. However, they do not report the EER of the system but report a False Reject Rate (FRR) of 1.7% and False Accept Rate (FAR) of 0%, which is not sufficient to compare the performance with other work.

Sun and Abdulla [17] combine Gabor filters with Curvelet transform features using a score level fusion method for matching using hamming distance. Gabor filters with 6 orientations were obtained and encoded into 3 bits. They reported an EER of 0.1023% Using the PolyU dataset. However, as this approach uses two methods to obtain a fused result this could be computationally expensive and may not be suitable for real-time systems.

A common limitation of all the aforementioned systems is that that they are sensitive to scale and rotation changes between the images. As palm vein images are subject to variations a scale and rotation invariant-based matching system such as SIFT is more suitable for palm vein recognition.

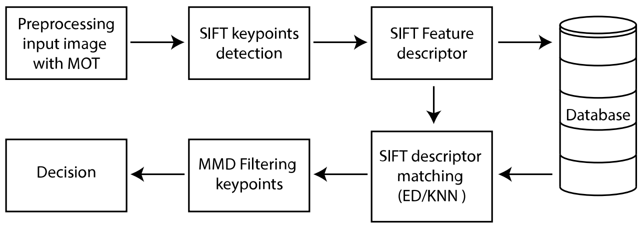

Figure 1: Proposed palm vein recognition system using MMD filter

III. THE PROPOSED METHOD

The workflow of the proposed palm vein recognition system is presented in *Fig*. 1. The extracted region of interest (ROI) of the palm vein images are first enhanced using the MOT image enhancement method. The extracted SIFT keypoints and descriptors are then stored in the database. At the feature matching stage, pre-processing and feature extraction steps were repeated, and then matched against the stored templates from the database and applied with the MMD filter.

A. *The Anatomy of SIFT*

SIFT analyses the scale-space of an image by employing variable scale Gaussian kernels[4]. The process starts with upsampling the input image by a factor of 2, and progressively blurring to generate layers of Gaussian images. Then each of the blurred layers are subtracted from the previous layer to generate difference of Gaussian (DoG) images. A set of these Gaussian images are referred to as an octave. This operation is repeated to generate an image pyramid. In the next octave, the last Gaussian image of the current octave is downsampled with a factor of 2 and used as the input image.

Each pixel in a DoG image is compared with its 8 neighbouring pixels of the current image, then with each set of 9 neighbouring pixels of the Gaussian scales below and above to identify local extrema to produce keypoints. Pixels which have larger or smaller values than all the neighbouring pixels are selected. A keypoint is accurately localized by analysing its nearby data for the scale, location, orientation and principal curvature ratio [6].

B. *SIFT Feature Descriptor and Matching*

The magnitudes and the orientation of the image gradient is first sampled around a keypoint to determine its orientation. The keypoint scale is used to calculate the amount of Gaussian blur required for the image. Then to generate the feature descriptor, gradient magnitudes and orientations are calculated from a patch of 16×16 pixels around the keypoint. To make the feature descriptor invariant to orientation, a Gaussian window is used to add weights to each pixel in this patch. The coordinates of this patch are rotated in relation to the detected keypoint orientation. Then the information calculated from 4×4 sub patches is used to produce 16 orientation histograms, each consisting of 8 orientation bins. To avoid the impact of sudden changes on the image, gradient information is interpolated into adjacent histogram bins To generate a feature descriptor, the histograms are formed into a 128-element vector and normalized to unit length to minimize the impact from illumination variances [18].

Feature matching is generally conducted by comparing these feature descriptor vectors. A feature descriptor of a keypoint from image A is compared with all the keypoints of

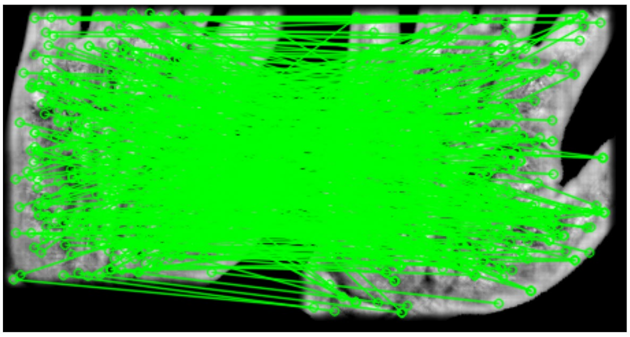

Figure 2: Closest-neighbor matching with SIFT + ED on the same subject.

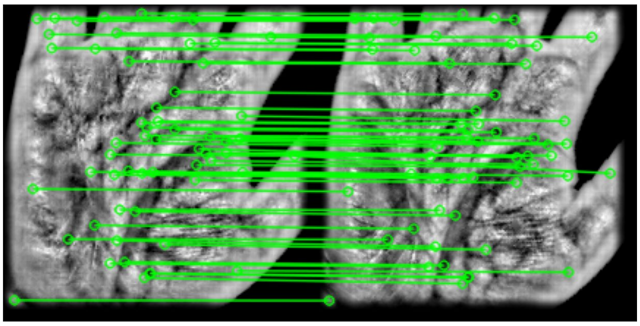

Figure 3: Second closest-neighbor match with SIFT + k-Nearest neighbor (KNN) + RT

image B to identify the closest match. The pair of points with a minimum Euclidian distance (ED) between their feature descriptor vector is selected as a match. This is referred to as closest-neighbour matching.

Fig. 2 demonstrates closest-neighbour matching with SIFT+ED of two palm images from the same subject consisting of 492 matches. A threshold can be used with ED to filter out the matches below a set value. However, this approach is not reliable as it can filter in many incorrect matches.

As an efficient solution to this issue, Lowe [6] suggests matching with the second closest- neighbour and comparing the distance ratio to determine a match. If this ratio is below a set threshold, the closest-neighbour keypoint pair is selected as a match. This is referred to as the ratio test (RT). *Fig. 3* demonstrates second closest-neighbour match with SIFT+k Nearest neighbour (KNN)+RT, using a distance ratio of 0.7 [6]. It can be observed from *Fig. 3* that with KNN+RT matching all the false positive matches have been filtered out.

Clusters of these keypoint pairs are used to perform a geometric fit into the images for object recognition [5]. However, as subtle changes in palm pose, finger or thumb positioning can introduce significant changes in the local area of a keypoint, using such point clusters are not suitable for palm vein recognition.

Further, *Fig. 4* demonstrates KNN+RT applied to palm vein image pairs of a different subject to that of *Fig. 3*. It can be observed from *Fig. 4* that KNN+RT has not filtered out some of the false positive matches, which will have a direct impact on the accuracy and the error rates of a palm vein recognition system.

C. Mean and Median Distance (MMD) Filter

MMD filter is based on the hypothesis that the distances between false positive match pairs should be greater than of the true positive matches, and that the x and y coordinate

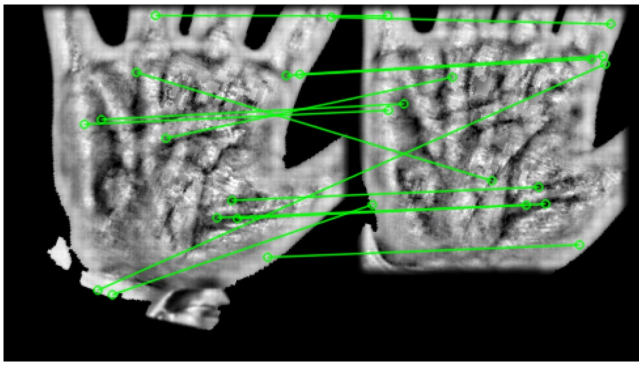

Figure 4: KNN+RT matching on the same subject. A considerable number of false matches are still preserved.

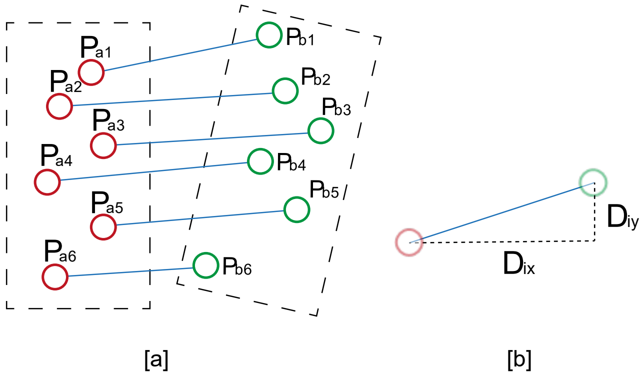

Figure 5: [a] Matched SIFT keypoints. [b] Horizontal (D_{ix}) and vertical (D_{iy}) distances between each pair of keypoints are calculated for the MMD filter.

distances of true positive match pairs should be minimal. When a pair of palm vein images are perfectly pre-aligned and superimposed on a cartesian plane, true positive match pairs should reside on the same x and y coordinates. Then the false positive matches could only be detected from different x and y coordinates, and the distance between these coordinates will be greater than 0. However, hand pose variations, image noise, rotation, and scale variations are still presented in pre-aligned palm vein images which can produce virtually infinite number of variations between two palm vein images of the same subject. As a result, the respective distances between x and y coordinates of a pair of true positive matches are always greater than 0.

This distance should not be confused with matching with the Euclidian distance of the SIFT feature descriptor. Feature descriptor distance checked by ED, KNN and RT is the Euclidean norm or the L2 norm of the differences. As discussed above, the SIFT feature descriptor is a 128-dimension vector. MMD filter is based on the geometric placement of SIFT keypoints. MMD filter checks the length of the space (as number of pixels) between respective x and y coordinates of matching SIFT keypoint pairs (*Fig 5[a]-[b]*). A similar geometric-based SIFT filtering technique for palm print recognition which is referred to as the SGR filter was presented in [19]. The SGR filter calculate the geometric distances and angles between every SIFT match. The MMD filter only calculate the geometric distance between the points using lesser computations and use algorithm to determine a match.

When matching SIFT features between two palm images g and p, for every matched keypoint pair (M_i), measure the horizontal (x) and vertical (y) distances (D_{ix}, D_{iy}) between their coordinates. Then calculate the respective mean (μ_x, μ_y) and

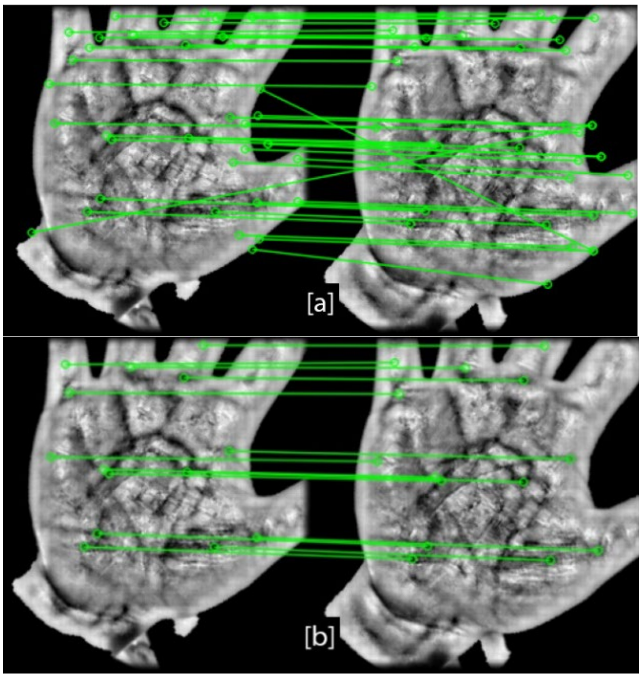

Figure 6: Matching on the same subject.
[a] KNN + RT
[b] KNN + RT + MMD

median ($\tilde{x}_x$, $\tilde{x}_y$) distances on both axes. Then count the respective number of match pairs when both of these distances are below or equal to the mean ($D_{ix} \leq \mu_x$ and $D_{iy} \leq \mu_y$) as N_L, and when both of these distances are above their respective mean ($D_{ix} > \mu_x$ and $D_{iy} > \mu_y$) as N_H. Two thresholds are introduced to accommodate rotation and scale variations of the images, as a maximum mean threshold (T_μ) and a maximum distance threshold (T_D).

The pseudo-code for the MMD filter is shown in **Algorithm 1** MDD Filter.

Algorithm 1 MMD Filter
Input: x, y coordinates of the matching feature points
Output:

```
for each M_i
        D_ix ← x_g-x_p
        D_iy ← y_g-y_p
end for
μ_x ← mean of D_ix
μ_y ← mean of D_iy
x̃_x ← median of D_ix
x̃_y ← median of D_ix
if (N_L > N_H) or (μ_x ≤ T_μ and μ_y ≤ T_μ)
        or (x̃_x ≤ μ_x and x̃_y ≤ μ_y) then
    for each M_i do
        if (D_ix < μ_x) and (D_ix < T_D)
                and (D_iy < μ_y)
                and (D_iy < T_D) then
            accept M_i as a true positive
        else reject match
        end if
    end for
    else reject the entire image
end if
```

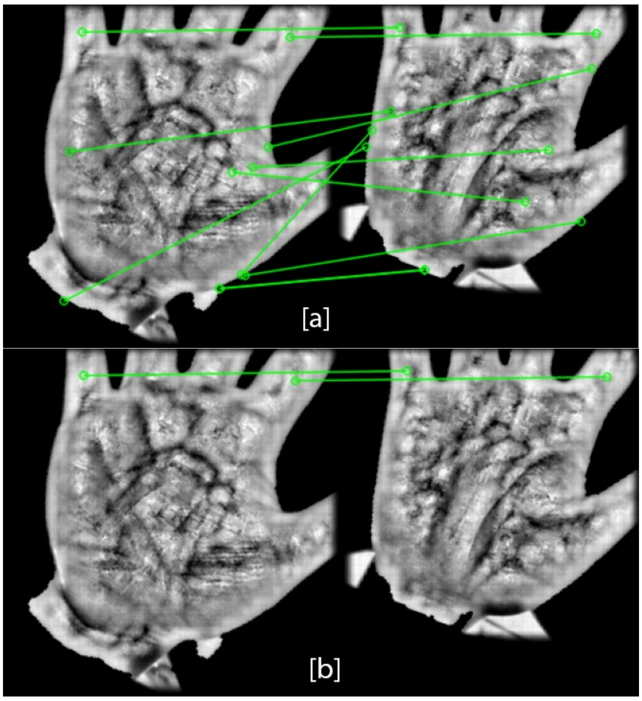

Figure 7: Matching on different subjects.
[a] KNN + RT
[b] KNN + RT + MMD

To consider if a pair of palm vein images are likely to belong to the same subject, one of the following conditions should be met. If not, the algorithm assumes that there are 0 positive matches and reject the image as a negative match.

- The total number of match pairs when their horizontal and vertical distances are below or equal to the mean, are higher than or equal to that of the total number of match pairs when these distances are above their respective mean ($N_L \geq N_H$).
- The horizontal and vertical mean values are equal or below their respective thresholds ($\mu_x <= T_\mu$ and $\mu_y <= T_\mu$).
- The horizontal and vertical median values are equal or below their respective mean distances ($\tilde{x}_x <= \mu_x$ and $\tilde{x}_y <= \mu_y$).

If the image meets with the above selection criterion, then to determine if a pair of keypoints is a true positive match, all the following conditions should be met.

- Horizontal distance is lower than the horizontal mean and the threshold ($D_{ix} < \mu_x$ and $D_{ix} < T_D$).
- Vertical distance is lower than the vertical mean and the threshold ($D_{iy} < \mu_y$ and $D_{iy} < T_D$).

Fig. 6 demonstrates SIFT matching on images from the same subject. In *Fig. 6[a]* SIFT features were matched using KNN and then applied with distance ratio (RT), In *Fig. 6[b]* the MMD filter was applied to *Fig. 6[a]*. When KNN+RT is applied to palm vein images from different subjects, a considerable number of false matches are still retained (*Fig. 7[a]*), and most of these false matches are filtered out when applied with the MMD filter (*Fig. 7[b]*).

From *Fig. 6[b]* it can be observed that the MMD filter has discarded all the false positive matches and some of the true positive matches. The thresholds T_μ and T_D can be adjusted to

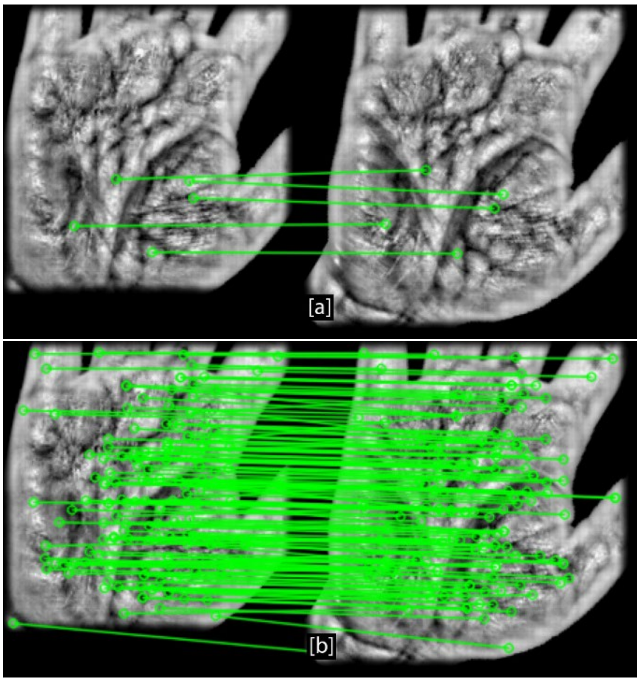

Figure 8: Effect of the threshold using ED+MMD.
[a] T_μ threshold set to 10 pixels with.
[b] T_μ threshold set to 25 pixels.

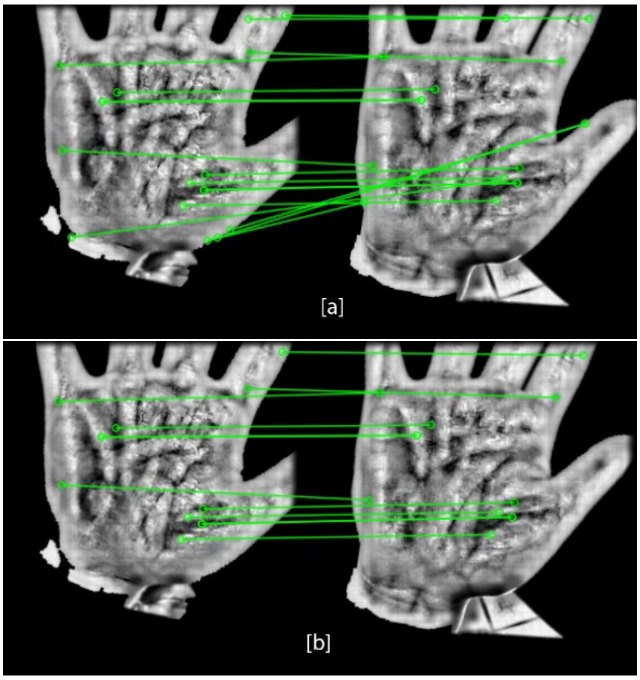

Figure 9: Matching with 0-degree rotation.
The T_μ threshold is set to 10 pixels.
[a] KNN + RT
[b] KNN + RT + MMD

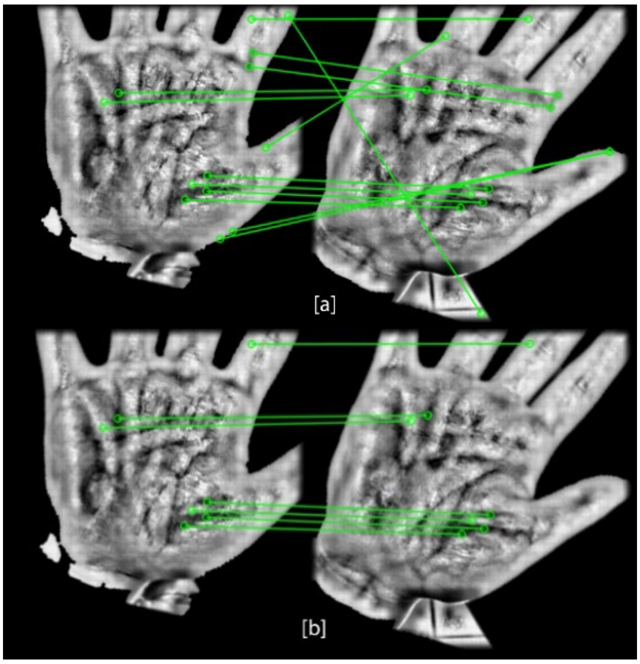

Figure 10: Matching with a 15-degree rotation to the image on the right. The threshold is set to 30 pixels.
[a] KNN + RT
[b] KNN + RT + MMD

control the sensitivity of the system as well as to accommodate the scale and rotational variances between the images.

Fig. 8 demonstrates how the thresholds can be used to control the sensitivity of the system. *Fig. 9* and *Fig. 10* demonstrate how the T_D threshold can be used to accommodate changes in rotation and scale. A fixed threshold of 25 pixels were used for T_μ. In *Fig. 9* pre-aligned images were used, in *Fig. 9[b]* a threshold of 10 pixels were applied to T_D and T_μ of the MMD filter.

In *Fig. 10* the right-hand side image used in *Fig. 9* were rotated by 15 degrees and a threshold of 30 pixels were applied to T_D and T_μ. The images already are in different scales as the whole palm has been used as the ROI.

IV. Experiments and Results

CASIA public dataset has been captured under 460, 630, 700, 850, 940 nanometres, and white lights, and contains 6 images per hand captured from 100 participants totalling 1200 images. Images are provided in JPEG format which contains lossy compression artifacts and image sensor noise. No skin damage or scars are visible in any of the images in the dataset. Vein images captured under the light of wavelengths between 820nm-880nm have better contrast [20]. Therefore, this research used the 850nm subset from the CASIA [21] multispectral dataset in 1 to many (1:m) closed set testing approach. A total of 240 images (20%) and 960 images (80%) of the dataset were used for training and testing respectively. Left and right hands were treated as separate subjects to maximize the sample count, except for the left and right palms from the same subject were not matched with each other.

For the experiments, all the images were first downsampled by 60%, and the entire palm was used for the region of interest (ROI), which produced variable sized ROIs. Thumbs and fingertips were identified using the convex-hull-based approach presented by [22]. A binary image was extracted by thresholding and using image contours, which were then applied with an erosion filter to produce a mask. Feature points detected close to the edges of the contour were filtered out. Images were pre-aligned prior to any processing.

The MOT method from [3] was used as the image enhancement method with 16×16 pixel image tiles. The performance of the MOT method was assessed by implementing several existing SIFT-based palm vein recognition systems. These systems base their experiments on the CASIA dataset. The 3 stages of a SIFT-based palm vein recognition system consists of are image enhancement, feature extraction, and feature matching. In [7] [8], the authors used ED with SIFT features, while [9] used ED+RANSAC and [10] used ED + bidirectional-matching. Further [8] used KNN + RT + bidirectional-matching with RootSIFT features. In [3] the image enhancement methods of the previous work were replaced with the MOT method to verify its performance. EER values were reported using multiple registration images (1-5) with ED, ED+RANSAC, KN+RT, and KNN+RT+RANSAC. To verify the performance of the MMD filter from this research, the benchmarking is based upon the results presented in [3] for SIFT descriptor matching and replaced the false positive filtering method with MMD. Thresholds of 25 and 30 pixels were used for T_{μ} and T_D respectively.

TABLE I. PERFORMANCE COMPARISON WITH EXISTING PALM VEIN RECOGNITION SYSTEMS. UNLESS OTHERWISE NOTED, THE RESULTS ARE PRESENTED USING 1 REGISTRATION IMAGE.

Recognition and filtering technique	EER %
(DoG-HE + SIFT) ED [8] (3 registration images)	(Left hand) 2.87
(MOT + SIFT) ED (3 registration images)	(Left hand) 1.478
(MOT + SIFT) ED + MMD (3 registration images)	(Left hand) **1.118**
(CLAHE + block stretch + SIFT) ED + RANSAC [9]	14.7
(MOT + SIFT) ED + RANSAC [3]	4.292
(MOT + SIFT) ED + MMD	**3.013**
ECS-LBP + SIFT (ED) [7]	(L/R hands) 3.12/3.25
(MOT + SIFT) ED [3]	(L/R hands) 2.75/2.876
(MOT + SIFT) ED + MMD	L/R hands) **2.46/2.622**

To find feature point pairs with minimum distances, Yan [10] applied a bidirectional feature matching method, where distance is measured between each feature point in the template to all points in the probe image (forward matching), and each feature point in the probe image to all points in the template image (backward matching). If a corresponding feature points pair from forward matching is reidentified from backward matching, and the Euclidian distance is below a set threshold the pair of points is accepted as a match. They report EERs of 0.65% and 1.84% for ORB and SIFT features respectively using 850nm images of the CASIA multispectral dataset.

In [8] KNN+RT was used with RootSIFT features and employed the bidirectional method from [10]. They further report results with SIFT+ED+Bidirectional-matching. They used the 850nm images from the CASIA dataset with 3 reference images to produce the matching template. They further reported an EER value using ED. SIFT+KNN+RT and RootSIFT+KNN+RT+Bidirectional-matching were used to verify the performance of the MOT method in [3]. However, the implantation of the Bidirectional algorithm in [3] performed poorly. The experiments with MOT+SIFT+ED recorded an EER value of 3.333% and performed better than MOT+SIFT+ED+Bidirectional matching which recorded an EER of 7.769%.

In [9] mismatches of SIFT+ED matching were removed with RANSAC. The reported EER value is 14.7% and the AUC is 90.8% using the CASIA dataset. [7] presented SIFT+ED matching and using ECS-LBP as the image enhancement method. They separated the left and right hand images into two subsets reducing the number of interclass matches by a factor of 0.5 resulting in lower EER values [3].

The parameters used in the aforementioned systems were not discussed except for [8] where they used a threshold of 0.8 with RT when using RootSIFT features. The performance comparison of the palm vein recognition systems is measured using the Equal Error rate or the EER and presented in Table I. The proposed MMD filtering method reduces the EER values against the compared filtering methods [9] [7] [8]. The RANSAC filtering based recognition method from [9] reported the highest EER value of 14.7%. Lowe [6] suggests that RANSAC filtering is not suitable when many outliers are presented.

The MMD filter was tested with ED+MMD and KNN+RT+MMD using 1-5 templates or registration images. Results are presented in Table II against ED and KNN+RT. The threshold used for RT in all the experiments is 0.7 [6]. EER values were reduced with every additional image used for the registration template. The highest performance gain was observed between ED and ED+MMD. When using 1 registration image, ED+MMD reported a higher EER of 3.013% than of 2.873% with KNN+RT. With 2-5 registration images ED+MMD reported better results than of KNN+RT. The lowest EER values are recorded when using the KNN+RT+MMD method (0.139%) followed by the ED+MMD method (0.194%) with 5 registration images. In [3] the MOT method outperformed the image enhancement methods compared from previous work. In this research, the MMD filter outperforms other filtering methods used in [3] with the MOT method. This confirms that the MMD filter outperforms the existing filtering methods used for SIFT-based palm vein recognition.

TABLE II. EER % VALUES WITH SIFT, USING 1-5 REGISTRATION IMAGES COMPARED WITH AND WITHOUT USING THE MMD FILTER

Registration images	ED [3]	ED+ MMD	KNN+RT [3]	KNN+RT+ MMD
1	3.333	3.013	2.873	2.326
2	1.677	1.459	1.725	1.448
3	1.715	1.31	1.663	1.257
4	0.53	0.232	0.61	0.265
5	**0.31**	**0.194**	**0.278**	**0.139**

V. CONCLUSION

Palm vein recognition is a challenging problem as palm vein images can produce an infinite number of variations due to the changes of the hand poses resulted from movements of fingers, thumb, and twist roll of the hand. The filtering methods proposed with current SIFT-based recognition systems still produce higher EER values.

This research proposed a novel filtering method referred to as the Mean and Median Distance (MMD) filter to filter out outliers or false positive matches of SIFT-based palm vein recognition, which is robust to variations in scale and rotation. The proposed MMD filter is based on the concept that if two images are aligned and superimposed, the geometric distance of the matching keypoints should be minimal. MMD filter check the mean and median distances separately in horizontal and vertical directions to accommodate the scale and rotation variations. The sensitivity of the filter can be adjusted using two thresholds.

Experiments were conducted using the MMD filter with Euclidian distance and the k-nearest neighbour and distance ratio test algorithms, using 1-5 registration template images. The results indicate that the proposed MMD filter outperformed the other filtering methods used with SIFT for palm vein recognition. Further, the MMD filter only requires performing a small number of calculations and low computations. The MMD filter is not limited to SIFT and can be used to filter the outliers from any type of feature matching. The MMD filter only consider the median and mean distances from the matching pairs. This can be further improved using machine learning techniques to learn these distances for true positive and false positive matches for a given dataset to improve the accuracy of the algorithm.

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