A Mosaic Approach to Touchless Fingerprint Image with Multiple Views

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ABSTRACT

Touch-based fingerprint technology causes distortions to the fingerprint features due to contact between finger and sensor device. Touch-less fingerprint technique is introduced in an effort to solve this problem by avoiding contact between the finger and the surface of the sensor. However, single contactless images of the finger leads to less captured features and less overlap between the different views of the fingerprint. In this paper, a new touchless approach for fingerprints based on multiple views images is proposed. Three fingerprint images are captured from the left, center and right side of finger using mobile camera. These three images are combined together using the mosaic method in order to construct a large usable area and increase the overlap area. The proposed method has been compared with other proposed touchless methods. Our touchless mosaic method has offered better performance and achieves more fingerprint features compare to single view touchless method. The proposed method has been evaluated using our touchless database that consists of 480 fingerprint images.

1. INTRODUCTION

The concept of finger identification is now popularly available in authenticating users because of its well-founded reliability and practicality in comparison with other biometric systems available in the market. It is already an accepted fact that fingerprint-based biometric has demonstrated itself as the best method in the business and with the largest market shares [1–5]. Obtaining fingerprint images is possible either in off-line or online method [6, 7]. The lifting of hidden fingerprints from crime scenes is a good example of offline method. The primary online method involves optical and solid state methods as well as thermal and ultra-sound procedures [8]. On the other hand, optical gadgets can be operated either through physical touching or by touchless mechanisms. Recently, a several of fingerprint image acquisition sensors in the form of optical and solid state methods as well as thermal and ultra-sound procedures are being applied in a wide variety of methods. But since these kinds of sensing devices are operated with touch-based methods, people utilizing them must have their fingers pressed or rolled on the surface of the plate before the images of the fingerprints could be captured. The drawback of this equation is that these capturing devices do not capture the precision images of the fingerprints as they should. They often capture degraded images because of the skin deformity due to skin elasticity and lack of uniformity in pressure when the finger is pressed or rolled on the surface of the plate. Other causes of this can be as a result of changes in the environment and the health or condition of the skin as well as hidden fingerprints left on the sensor surface [9–11]. Due to all these conditions, one fingerprint capture may now differ from the next capture of the same fingerprint which would definitely result in the performance of the authentication being unavoidably degraded. Also the rampant increase in fake or forged touch-based sensor techniques is creating a lot of issues as many people now concerned with health no longer want to use them or they try to avoid touch-based sensors due to hygienic concerns [8, 12].

To eliminate these problems, the idea of utilizing a fingerprint sensing technology has been proposed. This proposed technique is called touchless fingerprint image and it would no longer require making physical contacts with the sensor [13–17]. This will free the skin from becoming deformed as the information of the fingers minutiae and ridge can no longer change or suffer due to distortion. Because this is not being affected by different skin conditions, or hidden fingerprints, the images of the fingerprints will now become consistent. This brand of fingerprint device is not easily available in the market as it has a lower quality image when compared to the images of Frustrated Total Internal Reflection (FTIR). Its size is also very big when compared to the solid-state sensor. The pictures captured can exhibit reflections as the background is more complicated as it considers the skin as a component of the background. Only a limited part of the fingertip would appear when a picture of it is taken by a single camera and with the problem associated with perspective effects not disappearing [18]. The view difference of the finger shaped curvature and the limited common area existing between the fingerprints are the greatest drawback confronting these kinds of devices. There have been recommendations to tackle this problem by utilizing multi-view touchless sensing method. Mitsubishi Electric Corporation [14] suggested another touchless technique. Nevertheless, those types of sensing systems have an intrinsic problem since they use only one catching device including
CMOS or CCD cameras. Thus, incorrect characteristics can be captured in the side region and it decreases the accurate and beneficial region for authentication. Furthermore, it decreases the common area between degrades system performance and fingerprints if there is a view difference between images. The 3D touchless sensing systems that use more than one view have been discovered to solve this problem. TBS [15] suggested a 3D multi camera touchless fingerprint gadget called Surround Imager and Trade, by using five cameras to capture nail-to-nail images at one time and offered the rebuilt 3D finger shape. They offered a short explanation of the gadget design and associate algorithms related to 3D reconstruction and recognition. Nevertheless, the particulars of algorithms have not been provided and performance assessment has not been reported. Later, they went on to enhance their gadget and created a new form of products using three cameras at the same time. The detail stipulations of the gadgets and algorithms for image processing are not yet presented.

Choi et al. [19] proposed touchless method using one camera and two planar mirrors to create the multi view fingerprint imaging gadget. The side views of the finger reflected by these mirrors are seized by the central camera to create multi views of fingerprint images. The setting of the mirror and finger are supposed to be considered prudently because of varying size of finger. This kind of system has some problems. They divide the entire image into three sections manually. Continuous threshold is not appropriate to varying size of fingers. Also, they were based on stereo standardization for 3D reconstruction while the current methods for stereo standardization are in most cases based on distinct images captured by more than one camera. The efficient area in side-view images offered by mirror-reflected gadget is usually smaller than the one given by multi camera based gadget. These techniques did not raise a lot of interest in the market due to much higher prices in contrast to conventional touch-based sensors. Feng Liu et al [20] proposed image mosaicing approach based on an approach that utilizes several cameras. In this approach, an image acquisition is obtained using three cameras at the same time and LED lights. The aim of this method is to increase the active print area of fingerprint image. The main disadvantage of this kind of system is its costliness and difficulty for use as a practical system. It requires a complex system design in order to arrange the three cameras and different color LED and includes a complex hardware design. In order for the system to work properly, three cameras must be set carefully before capturing fingerprint images. There are also specific arrangements for light illumination that are used to capture images with uniform brightness.

In this work, we proposed an image mosaicing algorithm using a single camera which does not require any special arrangement for acquisition of the image. Our system works based on optical fingerprint images and does not require complex arrangements, making the system practical. However, we assume fingerprint image is captured by mobile camera indoor under normal light. We propose an algorithm for image mosaic from three fingerprint optical images. One fingerprint image is the center part of the fingerprint, the second image is the right side of the fingerprint image, and the third image is the left side of the fingerprint. However, the perspective distortion present in optical fingerprint images, which is due to the geometry of the finger, is a major problem. To solve this problem, two stage of image registration have been proposed. Our images are acquired in less constrained environment where a preprocessing step becomes necessary. In the first step, the fingerprint image region is segmented from the background using skin color information. After this, the ridges present in the fingerprint images is enhanced using ridge filters. After image enhancement, two stage image registration are performed. For image registration, the center image is used as a fixed image and the left and right side images taken alternately are used as moving images. In the first stage, we globally register the center and left side image using SIFT features. SIFT features are invariant to image translation, scaling, and rotation. In addition, they are robust to local geometric distortion and illumination changes. In this stage, our transformation is through the rigid type. First, SIFT features are extracted from both images then we perform features matching and transformation using RANSAC algorithm. RANSAC (RANdom SAMple Consensus) is usually used for parameter estimation and robust gains outlier presents in data sets. After performing global image registration, we use these global parameters as initialization of our next stage registration, which takes care of local distortion presents in the image. We assume that our transformation is a projective transformation, which is able to handle the local distortion that usually presents due to the shape of the finger. In this stage, we use intensity based image registration using normalized mutual information and gradient decent optimization. After registration, the moving image is transformed into fixed image space and create mosaic. We apply the algorithm for the center and the other left and right sides image to create a mosaic of three images. First, we create a mosaic between the center and left side image, then between the center and right side image. We always use the center image as the fixed or anchor image because it captures the maximum region compare to the other two images. The detailed description of algorithm is given below. Our proposed method and touchless capturing technique is described in section II. In section III, we provide details about fingerprint preprocessing. Section IV provides details about two stage of image registration. In section V, we provide details about image resembling and mosaic generation. Experiment and results are discussed in section VI. Section VII concludes the paper and discusses future directions.

2. MULTIVIEWS METHOD USING THREE CAMERAS

As shown in Figure 1, a single fingerprint image usually shows only one side of the finger, which is the center of the fingertip. In such cases, the features in the center are extracted correctly while the features at the edge are missing or considered as false minutiae points since the ridge ends abruptly [21]. Furthermore, contactless image that are collected from single views have less features compared to combined images from different views. According to our fingerprint capturing method, three images are captured using mobile camera from left, center and right side of finger shown in figure 2. For each single view, minutiae points usually occurred in the center of the image and decreased towards the sides due to lack of image quality. To overcome this problem, a combination of multi views of touchless fingerprint
image is introduced. In contrast to the previous described applications, our method does not require additional hardware or complex arrangements. As shown in Figure 3, one smart phone camera can be used to capture three different image views of fingertips in different times. We used an Apple iPhone 4s rear camera with 8 megapixels and 3264x2448 pixels, where pixel size is 1.4 $\mu$m and 1/3.2" is the sensor size in our experiment. To obtain high quality fingerprint images and large overlap between the center and the side images, two assumptions are considered. First, the position of the mobile camera during capturing left or right sides is considered based on the camera position when center image is captured. Different angles are considered in the previous proposed algorithms with 15, 30 and 45 degrees. Smaller angles can increase the overlap area between three side images. We assumed the mobile camera and the finger are fixed at the time of image capturing and the camera is focused on the center of the image. In contrast, fingerprint features on the far sides can be missed if the angle is small. In the proposed method, the angle of the camera can be in the range between 15 degree and up to 25 degree. Secondly, the distance between the finger surface and the camera is important as it affects the quality of the obtained image. Although the automatically focus of the camera increase the quality of the obtained image. In our method, the distance can be varying between 7.5cm and 12cm. In this case, we can obtain good quality images even if the camera focus is not adjusted. The images captured from mobile phone cameras usually suffer from motion blurring problem that can corrupt the quality of an image seriously. In the first step, blur is removed from the image by using Wiener filter based deblurring approach [22]. The Wiener filter approach is an inverse filtering based approach and it is useful in order to remove additive noise and blur from image. In our experiment, Wiener filter minimizes the mean square error while removing blur from image. Frequency domain formulation of wiener filter is defined as:

$$Wf(l_1, l_2) = \frac{P^*(l_1, l_2)K_{ii}(l_1, l_2)}{[P(l_1, l_2)]^2 + K_{ii}(l_1, l_2) + K_{ii0}(l_1, l_2)} \quad (1)$$

where $K_{ii}(l_1, l_2)$ and $K_{ii0}(l_1, l_2)$ are the image spectra power and noise respectively. $P(l_1, l_2)$ is the blurring filter.

In second step, segmentation of the fingerprint region from the background is applied. In this step, we use skin colour properties and apply segmentation in other colour domains as there is little difference between RGB skin colour and its background. To apply colour segmentation, RGB colour of fingerprint images are converted into YCbCr color domain fingerprint images [23]. After converting the image into YCbCr colour space, thresholding is applied into croma (Cb and Cr) domain due to the fact that skin colour shows a significant difference from background colour in this domain. In the third step, ridge enhanced filters are then applied in order to enhance the ridges in the fingerprint image which has the following steps:

1. Normalization: Usually a fingerprint image does not show a good contrast. To improve the contrast of fingerprint images, empirically defined mean and variance value are determined by normalizing the input fingerprint image.
2. Estimation of image orientation: The orientation is an intrinsic property of fingerprint images which defines the ridge and farrows in terms of invariant coordinates. There are lots of approaches are available to estimate orientation images. For the purposes of this experiment, the approach given by Lin Hong [24] has been used.
3. Ridge frequency determination: The ridge frequency can be defined as a frequency in the local neighbourhood fingerprint region, which does not contain minutia points. Grey levels along ridges modeled as normal sinusoidal waves which are perpendicular to the orientation direction. In this stage, Lin Hong approach is also used to calculate the ridge frequency image. Bandpass filters are then applied using Gabor filters.

3. **PREPROCESSING**

Preprocessing becomes vital step for the proposed work because contactless fingerprint image does not show the significant features. In the proposed algorithm, SIFT algorithm is used for image feature registration. In order to introduce accurate image registration, accurate features extraction is required. Therefore, preprocessing stage is necessary and involves three steps:

1. Image blur removal.
2. Region of interest (ROI) segmentation.
3. Ridge enhancement.
The parameters of Gabor filter will tune with the help of orientation and ridge frequency image by using approach given by Lin Hong. The original image, ROI extracted image, and enhanced image (blur removal and ridge enhancement) are presented in Figure 4.

![Figure 4: (a) Original Image (b) ROI image (c) Enhanced Image](image)

4. IMAGE REGISTRATION

Image registration refers to transforming one image to another image domain in order to combine both images easily. In this work, two stages of image registration called global and local mapping are implemented. Three images of same finger are used: center, left, and right sides of finger. The center image is always used as the fixed image and the other two images are used as moving images. In the first step, image registration is applied to estimate the global parameters. Taking into account that rigid transformation indicates scaling and rotation that presents in moving images as compared to fixed images, we assumed rigid transformation between the fixed and the moving images [25]. This step will align the images at the coarse level. In consideration of the structure of fingerprints, the Coarse registration step alone is not sufficient. Fingers are curved objects, rather than flat, therefore they introduce elastic distortion in acquired images. To solve this problem, we estimate the local parameters between images, while assuming projective transformation. This step will align images at a local level, such as ridge patterns, etc. Center image is considered as the anchor image in order to register the center and left image, then center and right image.

4.1 Global mapping

Global mapping refers to the registration of the fixed and the moving images using global parameters which are applied to all pixels of moving image. In this step, the outer boundary of the moving image is treated and register with the fixed image. For this purpose, feature based image registration is used while assuming rigid transformation presents between fixed and moving images. Features are calculated using a SIFT descriptor [25] for both fixed and moving images. After that, matching points between fixed and moving images are determined while the model parameters are estimated using the RANSAC algorithm [26]. In the SIFT approach, there are four major stages that translate the data of the image into scale-invariant coordinates in relation to the local characteristics. These stages include the detection of scale space extrema, localization of key point, assignment of orientation, and the description of key point. We assume $F(k,l)$ represents an image and $S(k,l,\sigma)$ the scale space of $F$, which can be represented as:

$$S(k,l,\sigma) = V(k,l,\sigma) \ast F(k,l)$$  \hspace{1cm} (2)

where $\ast$ is the convolution operation in x and y. $V(k,l,\sigma)$ is a variable-scale Gaussian and is defined as:

$$V(k,l,\sigma) = \frac{1}{2\pi\sigma^2}e^{-\left(k^2+l^2\right)/2\sigma^2}$$  \hspace{1cm} (3)

In this experiment, the detection of scale-space extrema starts with local maxima and minima recognition of and of $C(k,l,\sigma)$, which is referred to as the convolution of a variance of Gaussian with the image $F(k,l)$.

$$C(k,l,\sigma) = (V(k,l,\sigma) - V(k,l,\sigma)) \ast F(k,l)$$

$$= S(l,l,\sigma) - S(k,l,\sigma)$$  \hspace{1cm} (4)

In order to detect the points that are local extrema, we performed comparisons with the nearest 26 neighbours (8 neighboring points of the same scale and its 9 neighboring points vertically along the above scale and below scale). These points also invariant to the range, direction of the detection, and image locations. If this value is a less than all other points, it called key point. Scale-space extrema detection creates large number of key points and out of these key points some of them are unstable. The next step is to reject unstable points and this process is called localization. This step needs information about location, scale and principal curvatures to doing localization. All the key points with low contrast are rejected based on a threshold, or those whose localization is poorly performed along with the edges. The next step is to reject points based on curvature when poor localization is used in removal of extrema. To reject the points, we calculate largest and smallest Eigen vector (based on the product of 2x2 of Hessian Matrix of $C(k,l,\sigma)$ on the key point location) and reject the key point occurs whenever this point occurs lower than the largest and smallest Eigen vector.

The assignement of the orientation of the key points is the next SIFT step. This assignment is based on the local gradient directions of the image. The magnitude and direction determination of the gradient are calculated for every pixel in a neighboring region around the key point in the Gaussian-blurred image. Each of the key points relative to the orientation is thus become invariant to the rotation of the image. This is made possible by the use of an orientation histogram obtained from the gradient orientation of the key points, which are in the region surrounding the key point, and with 36 bins within the range of the 360 degrees orientation. Gradient magnitude and Gaussian weighted using a value 1.5 times more than the key point scale is used in weighing of each of the samples in the histogram. In the accurate determination of the key points, a threshold-based procedure is made into use. SIFT features are as shown in Figure 5, on a developed fingerprint image.

![Figure 5: SIFT features on fingerprint image](image)
2D rigid registration is defined as:

\[
\begin{pmatrix}
  x' \\
  y'
\end{pmatrix} = \begin{pmatrix}
  \cos\Theta & -\sin\Theta & t_x \\
  \sin\Theta & \cos\Theta & t_y \\
  0 & 0 & 1
\end{pmatrix} \begin{pmatrix}
  x \\
  y \\
  1
\end{pmatrix}
\]  

(5)

where \((x, y)\) denotes the initial point and \((x', y')\) denotes the altered point. \(t_x, t_y\) are the translation parameters in x and y directions and \(\Theta\) is rotation angle in a counterclockwise direction. In this step, we find the SIFT key point and its corresponding descriptor in both images (fixed or moving image). After finding the SIFT point, feature matching step is applied. For matching SIFT points and transformation estimation, a RANdom Sample Consensus (RANSAC) technique is applied. This approach finds solution using minimum number observations/data point. RANSAC [26] is insensitive to outlier and initial alignment. In RANSAC, some random sets of points are chosen and global parameters are estimated based on these points. This process applies iteratively and the algorithm finds the most stable sets of points that enable us to estimate the final transformation parameters based upon stable points. These estimated parameters work as initial points for the next stage registration step. Figure 6 shows the final match between two fingerprints. Most of these matches are good under rotation conditions.

Figure 6: SIFT features matching

4.2 Local mapping

Second stage of image registration called local mapping. The aim of local mapping process is to register fixed and moving images at the local level and ridges will properly align. In this step, distortion presents inside region of fingerprint images is eliminated. Local mapping framework is shown in figure 7 and has the following steps:

1. Similarity measure.
2. Optimization method.
3. Transformation model.

(i) Similarity Measure: Similarity measure determines how closely two signals/images are related. The higher the score of the measure, the better is the alignment between the images or specific window pairs. Similarity measures are used as objective function. Normalized mutual information is used as the similarity measure, which is defined as:

\[
N(X, Y) = \frac{E(X) + E(Y)}{E(X, Y)}
\]

(6)

X and Y represent the moving images while \(E(x)\) and \(E(Y)\) denote the entropies of X and Y. Equally, \(E(X,Y)\) signifies the dual entropy of A, B.

(ii) Optimization: In order to find the maxima of a similarity measure or minima of dissimilarity for given set of transformation parameters exhaustively over the entire transformation space, the space explodes with the increase in the degrees of freedom. Brute force may be used when the transformation includes only translation, but in the case of higher transformation models, an optimization framework is required in order to localize the maxima. Various optimization methods have been used in literature for image registration, including Gauss-Newton minimization, gradient descent, Levenberg-Marquardt, as well as others. We are using the gradient descent based optimization approach.

(iii) Transformation model: Transformation models are based on the distortion present in the images. In this experiment, the parameters of the transformation model are estimated, and then applied to the moving image in order to transfer into the fixed image domain. While considering local mapping, we assume that our transformation model is projective which defined as:

\[
x' = \frac{k_0 + k_1x + k_2y}{1 + m_1x + m_2y}
\]

(7)

\[
y' = \frac{l_0 + l_1x + l_2y}{1 + m_1x + m_2y}
\]

(8)

where \((x, y)\) is the initial point or fixed image point and \((x', y')\) is the transformed image or moving image point. The parameters to be estimated are: \(k_0, k_1, k_2, l_0, l_1, l_2, m_1, m_2\). Projective transformation has 8 parameters and requires four non-collinear corresponding pairs in order to estimate the parameters. In the proposed method, initial values come from global parameter mapping.

Figure 7: Local mapping framework

5. IMAGE TRANSFORMATION AND MOSAIC GENERATION

Once the parameters have been estimated, the next step involves the change of the image in motion into coordinates of the fixed image using resampling. The change can be understood as onward or backward mapping. The onward mapping approaches are often complex to employ and can result in perforations. As a result, backward mapping techniques become the better choice. During transformation of the moving image into the fixed image space, some of the moving image points falls in between grid values (discrete image grid). These intermediate values creates holes in the image. To estimate these intermediate values and to fill these holes, interpolation step required. Interpolation is performed using convolution operations and interpolation kernels. The ideal kernel is a 2-D sinc function, which is difficult to implement due to the infinite extent of the function. Thus, approximations are used in order to reduce the computational cost. The popular interpolation functions are bilinear, bicubic, quadric splines, cubic splines, and Gaussians. These interpolation schemes are usually subjected to a trade-off between accuracy and computational cost. In
the proposed algorithm, Bicubic interpolation function [27] is used and given as:

\[
p(x, y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^i y^j
\]  

where \(p(x,y)\) is the interpolated surface, and \(a_{ij}\) is the coefficient, which is the estimate for interpolation, and \((x,y)\) is the image pixel co-ordinates. Right side image and left side image have different polarities; therefore, for the mosaic creation, we first flip one of these two images horizontally. After that, blending function is performed to create the mosaic of images as follows:

\[
I_{\text{blend}} = \alpha I_{\text{center}} + (1 - \alpha) I_{\text{left}}
\]

where \(\alpha\) is blending parameter. In our experiment, we assign 0.5 value to \(\alpha\). \(I_{\text{blend}}\) represents the final blending image; while \(I_{\text{center}}\) indicates the center fingerprint image; and \(I_{\text{left}}\) refers to the left fingerprint image. We then apply the same function to blend the right side image. In this procedure, we apply the center image to the left side image and the center image to the right side image. In this case, the center image is fixed, while the left and right side images are moving images respectively.

6. EXPERIMENT AND RESULTS

In this paper, we have proposed an algorithm to create image mosaic from mobile phone camera images. For testing purpose, we have build our touchless database which contains 480 fingerprint images from 20 persons. For each person, 8 fingers are investigated by capturing three fingerprint images from three views and then 160 mosaic images are created for each finger. We know that contactless fingerprint images have less features (such as minutia points) compared to contact-based fingerprint images. In this case, single view is not sufficient for recognition purpose because it does not have sufficient features. Therefore, we are using three views of fingerprint images, which includes center, left, and right view in order to generate mosaic image. Pre-processing stage is important process due to the fact that contactless fingerprint image has less features. As described in the previous section, image registration and mosaic generation steps are performed after preprocessing step. While creating the mosaic image, we blended one of the images in order to see how much area increased due to mosaic and how well our images are aligned. To evaluate our algorithm, we performed three different experiments. In the first experiment, minutia points are calculated in single and mosaic images in order to estimate the percentage gain of true minutiae points in mosaic images. In the second experiment, we have tested the recognition capability of mosaic images by considering fingerprint as biometric measure. In this experiment, we show that mosaic images are useful for person authentication purpose by using minutia points and SIFT features based approach. In third experiment, we have compared the change in the region of interest(ROI) or effective area between single view and mosaic image. ROI area is directly proportional number of features, if ROI is more then number of features are more and vice versa. These features use later for different application purposes.

6.1 Minutiae points extraction

In this experiment, the number of true minutiae points is calculated in each individual image (center image, left side image, right side image) and the mosaic image generated from our algorithm. Minutiae points are very important feature that represents the effectiveness of fingerprint images as biometric identification. High numbers of true minutia points indicate that the fingerprint image is good for biometric identification purposes.

In order to extract the minutia points, we binalized the fingerprint image and applied morphological operation thinning and closing. Then, we searched for minutia points using window operations. After finding all minutia points, false minutia points are rejected based on thresholding. Figure 8 shows the extracted minutiae points in the three different single views and in our mosaic image. Mosaic image presents more minutiae points compared to any single view image.

Figure 8: (a) Left side image (b) Center image (c) Right side image (d) Mosaic image.

Figure 9 shows the variation of minutia points in 10 random mosaic images compare with corresponding single view images. Due to center image shows more features compared to left view or right view, center image and mosaic image are used in order to compare number of minutia points. This experiment shows that we gain an average of 20 more minutia points in mosaic images as compared to center fingerprint images. Usually contactless fingerprint images have fewer minutia points and this conclusion will help to establish mosaic fingerprint images for biometric identification purposes. Figure 9 shows the number of minutia points present in the three individual images (left, right and center) as well as the mosaic image. Mosaic image shows more features compare to all other singe view images.

6.2 Recognition accuracy of mosaic image

In the second experiment, we tested our mosaic image as a biometric measurement. For comparison purposes, we took the center, right side, and left side images individually and created mosaic image which is used as biometric measurement. For testing purposes, we took a new fingerprint image of a person and called it input image and then compared it with the four images (3 individual and one mosaic image). These 4 images can be treated as individual images. Minutia points are then extracted from input image and from the four images as well. After that, extracted features of input image are matched with each image of the four images separately using the Euclidean distance similarity measure which determines the similarity between two fingerprint images. We calculated the accuracy of all four types of images.
Figure 9: Comparisons between number of minutiae points in left, right, center and mosaic image

and table 1 shows the results of the recognition accuracy. In this table, we see that because of the mosaic image, we have the highest number of minutia points and the recognition accuracy increased significantly. We also compared our algorithm with other three mosaicing algorithms by testing all of the algorithms on our database. We used two types of features which are minutia based and SIFT point based for recognition purpose [28] [29] since these approaches are extensively used in literature for fingerprint recognition purpose. In both approaches, we used Euclidean distance as similarity measure. Table 2 shows that our algorithm performs better compared to others. The main reasons for better performance of our algorithm is we take care both global and local distortions presents in fingerprint images.

Table 1: Recognition accuracy

<table>
<thead>
<tr>
<th>Type of image</th>
<th>Recognition accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center image</td>
<td>93</td>
</tr>
<tr>
<td>Left side image</td>
<td>89</td>
</tr>
<tr>
<td>Right side image</td>
<td>88</td>
</tr>
<tr>
<td>Mosaic image</td>
<td>97</td>
</tr>
</tbody>
</table>

Table 2: Recognition accuracy of mosaic image compared with the other approaches

<table>
<thead>
<tr>
<th>Method</th>
<th>Minutia accuracy (%)</th>
<th>SIFT accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>H. Choi et al. [19]</td>
<td>94.1</td>
<td>95.2</td>
</tr>
<tr>
<td>Feng Liu et al. [20]</td>
<td>95.6</td>
<td>95.8</td>
</tr>
<tr>
<td>Our approach</td>
<td>97</td>
<td>97.5</td>
</tr>
</tbody>
</table>

6.3 Finger active area increment

One of problems in the contactless fingerprint images are to capture less fingerprint area that are useful for recognition purpose. In this experiment, the total effective area after creating mosaic image will increase and this will help for recognition task. One of the advantages of creating the mosaic is that the region of interest (ROI, which is an area useful for extracting features for recognition purposes) is bigger compared to single view fingerprint images. To calculate the ROI, we extracted the finger region to apply segmentation using skin colour properties in the YCbCr domain. After that, we apply canny edge detector [30] to find the outer boundary of fingerprint images. Canny edge detectors have less error rates and good localization. In canny detection, the image is smoothed firstly using the Gaussian filter. After that, we calculate the gradient, nonmaxima suppression, and applied thresholding. To calculate the area, the number of pixels inside the outer boundary which represents the ROI is calculated. Table 3 shows the results of average area of 20 test images.

Table 3: Finger active area increment

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Area (number of pixels)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center part image</td>
<td>45244</td>
</tr>
<tr>
<td>Right part image</td>
<td>38678</td>
</tr>
<tr>
<td>Left part image</td>
<td>39567</td>
</tr>
<tr>
<td>Mosaic image</td>
<td>55443</td>
</tr>
</tbody>
</table>

In table 3, we compared the average area of 20 test images. For comparison purposes, we used three views of fingerprint images and a mosaic image was created using these three images. The average gain of area is around 15% in the mosaic image from the center part image. This gain is very important, as the area of interest is usually directed propositional to recognition accuracy. If area is greater, then recognition accuracy is also high. In this work, after creating mosaic, our ROI area increased. This shows that this region is more reliable and accurate.

7. CONCLUSION

In this work, we proposed an algorithm for fingerprint image mosaicing using three touchless fingerprint images with different views. In our algorithm, mobile camera is used to capture touchless fingerprint images. We used two stage image registration: one for global registration and one for local registration. Our algorithm parameters works with less constrained environment, where there are no special acquisition environments. Mosaic image improves important features presents in fingerprint images and increased the overlap area between different images view so that recognition accuracy also improves. We tested our algorithm on our created database and show positive results. One drawback of our algorithm is that it does not perform well when there is little overlap between images because we are not able to extract enough SIFT features to estimate global parameters. In future work, we need to improve our algorithm to work with lower overlap. For this, we need to find new feature, other than SIFT, which is able to estimate parameters under lower overlap conditions.

References


