Abstract—To solve the problems associated with conventional 2-D fingerprint scanners such as skin deformation and print smearing, in this paper we introduce a non-contact fingerprint scanner employing structured light illumination to generate high resolution albedo images as well as 3-D ridge scans. The question to be answered in this research is whether or not, ridge depth information improves the quality and matching capability of acquired fingerprints? For evaluation of this question, we use the National Institute of Standards and Technology fingerprint image quality metrics. These metrics require the 3-D prints to be flattened. We present a complete and detailed flattening algorithm based upon unfolding an elastic tube fit to the peaks and valleys of ridges identified within the scan. Further improvement of the flattened print is achieved through the incorporation of ridge information extracted from the albedo image with the depth and albedo ridge information fused together according to local scan quality. Our study compares image quality between the flattened 3-D prints and ink rolled prints. Most significantly, the matching performance of 3-D flattened to 3-D flattened prints is evaluated based on ridge depth only, albedo only and depth with albedo fusion.

Index Terms—3-D fingerprint, flatten, depth, albedo, fuse

I. INTRODUCTION AND PREVIOUS WORKS

Fingerprint, due to their uniqueness and immutability, have been applied to identify criminals in law enforcement and, currently, are increasingly being used for personal identification in civilian applications [1]–[4]. Systems for automating fingerprint matching are generally described in terms of data acquisition, post processing, and registration [5], [6]. Among these three parts, data acquisition is generally regarded as the most critical because of its great effect on overall system performance [5]. Traditionally, fingerprint images are acquired by pressing or rolling a finger against a hard surface (e.g., glass, silicon, polymer) or paper (e.g., index card). Aside from obligatory maintenance of the sensor/prism surface, these contact-based scanners often result in partial or degraded images [7]–[13], due to:

1) uncontrollability and non-uniformity of the finger pressure on the device;  
2) permanent or semi-permanent change of the finger ridge structure due to injuries or heavy manual labors;  
3) residues from the previous fingerprint capture;  
4) data distortion under different illumination, environmental, and finger skin conditions;  
5) loss of surrounding information in technologies without finger rolling;  
6) extra scanning time and motion artifacts incurred in technologies that require finger rolling.

The majority of these limitations arise due to the physical contact of the finger surface with the sensor plate, or the nonlinear distortion introduced by the 3D-to-2D mapping during image acquisition [14].

To eliminate the many drawbacks of contact-based scanning, several novel technologies have been developed [15]–[19] that avoid direct contact between the sensor and the skin, and thus, consistently preserve the fingerprints “ground-truth” without skin deformation during acquisition [20]. In [17] and [18], Parziale et al proposed a multi-camera touchless fingerprint scanner which acquires different finger views that are combined together to provide a 3-D representation of the fingerprint. Due to the lack of contact between the elastic skin of the finger and any rigid surface, the acquired images present little deformation [18]. However, based on the shape-from-silhouette scanning technique, the 3-D ridge information cannot be obtained, and the ridge information is obtained from the surface reflection variation (i.e. albedo) information. Thus, the fingerprint is affected by surface color, surface reflectance, geometric factors and other effects.

In this paper, we employ a non-contact, 3-D scanning method of structured light illumination (SLI) through phase measuring profilometry (PMP) [21]–[23] to make a 3-D scan of the human finger with sufficiently high resolution so as to record 3-D ridge-depth information. Compared to other structure light algorithms like De Bruijn sequences [24], binary codes [25], or gray levels projection [26], the PMP technique exploits higher spatial resolution [27], which can achieve a given precision with fewer frames.

Now because our scanner captures fingerprint ridges and valleys as they contour a cylindrically shaped finger, corresponding fingerprints must be virtually flattened in order to be backwards compatible with existing recognition/matching systems, which have evolved around contact-based scanning. In general, the flattening problem has been studied by cartographers, like Gerardus Mercator, for hundreds of years and is well known as the map projection problem [28], [29]. A map projection refers to any method of representing the surface of a sphere or other shape on a plane [30], [31]. Besides globe unwrapping which has been heavily studied in Geographic Information Systems (GIS) [28], [29], some other applications of 3-D object flattening include medical imaging, surface recognition and industrial design [32]–[34].

All flattening methods distort the surface in some fashion. However, different map projections exist in order to preserve some properties of the 3-D body at the expense of others [29],
And these flattening approaches can be roughly classified into parametric and non-parametric methods. While parametric methods try to project the 3-D object onto a parametric model, e.g., a cylinder, and then flatten the model, non-parametric methods apply the flattening directly to the 3-D object [29], [35]. Thus, the non-parametric methods are typically employed for irregular shaped objects, and the parametric methods are often used for certain shaped objects. Since the parametric methods are more straightforward and their computational cost is lower, the parametric methods are preferred if a close 3-D model can be chosen for the object.

For this specific problem of 3-D fingerprint flattening, some computational approaches have been proposed. Most namely, Chen et al. obtain the 3-D fingerprint model and propose an unwrapping approach in [35]. Their “Equidistance Unwrapping” approach flattens the 3-D model in such a way that it resembles the effect of virtually rolling the 3-D finger on a 2-D plane; however, using the shape-from-silhouette scanning technique [17], [18], the accurate and detailed 3-D information of a point cannot be obtained. Thus, Chen’s ridge information is actually derived solely from albedo images. So applied to a system like ours which records both albedo and 3-D ridge depth information, the method of equidistance unwrapping would ignore half of the readily available ridge information, that is provided by detailed 3-D depth information.

In order to take full advantage of the ridge information provided by our scanner, we have been looking at a range of flattening methods that work in 3-D space to virtually unravel the depth detailed 3-D fingerprint, while maintaining the higher frequency, low amplitude ridge fluctuations. The first such algorithm, the springs algorithm [36]–[38], was based upon a web of virtual springs spanning the fingerprint surface where, first, ridges were extracted from the surface. The remaining 3-D point cloud was then treated as a mechanical system in which points had mass, and these points of mass were inter-connected by means of mechanical springs. The mesh was then pressed down onto a flat plane. As a non-parametric method, the computational cost of the springs algorithm was high.

To reduce the computational cost, another algorithm, the fit-sphere algorithm proposed by Wang [39], relied upon best fitting a sphere to the fingerprint scan where the original 3-D data was converted to spherical coordinate \( \{ \theta, \phi, \rho \} \). A \( \theta \) and \( \phi \) map was then created so that the 3-D fingerprint surface was mapped onto a plane with minimal distortion.

Noting that fingers are more tubular than spherical in shape, this paper presents a novel flattening algorithm which unravels a deformable tube that, unlike its predecessors, incorporates ridge information obtained from both depth (Sec. III) as well as albedo information (Sec. IV), fusing the two if they were separately flattened prints (Sec. IV). Thus, the fused 2-D print takes advantages of both detailed depth and albedo information. This paper describes the 3-D acquisition setup in Sec. II. The results in Sec. V demonstrate that the 3-D prints are successfully obtained and flattened into 2-D prints such that high quality and registration performance is achieved for both depth flattened and albedo flattened prints when applying the matching software developed by the NIST.

Most significantly, fusing the 2-D prints, based upon local scan quality, achieves higher performance than either prints obtained solely from depth or albedo.

II. DATA ACQUISITION

The system under study was developed by Flashscan3D LLC. and the University of Kentucky. Figure 1 shows the flowchart of 3-D data acquisition, processing and evaluation for the scanner. The system takes about 0.7 seconds to obtain a 5 million point, 3-D fingerprint image and less than 1 second for the overall data processing. The scanning portal size is 35 mm along the length of the finger and 32 mm across. The sample spacing is about 1,344 ppi which is later downsampled to exactly 500 ppi after flattening.

![Flowchart for the single fingerprint 3-D data acquisition, processing and evaluation.](image1.png)

![3-D fingerprint acquisition using PMP technique.](image2.png)
expressed as [22], [23]:

\[ I_k^p(x^p, y^p) = A^p + B^p \cos(\phi(x^p, y^p) + 2\pi k/K), \]  

where \((x^p, y^p)\) are the projector coordinates, \(A^p\) and \(B^p\) are projector constants, \(\phi(x^p, y^p)\) is the phase of the reference sine wave pattern which is assigned as:

\[ \phi(x^p, y^p) = 2\pi f \frac{y^p}{L}, \]  

where \(f\) is the frequency of the sine wave, and \(L\) is the length of the sine wave. The subscript, \(k\), in Eqs. (1) and (2) represents the phase shift index where the total number of phase shifts is \(K\), and the superscript, \(p\), signifies that this is the projected pattern. A single frequency pattern is used with a total of \(K = 10\) phase shift patterns. The frequency of 16 cycles per length of each pattern is chosen to achieve and approximate a spatial period of 1.2mm on the finger surface. This frequency is a trade-off between the upper optimum frequency [40] and yet low enough to avoid interference with the average fingerprint ridge frequency. 

From the viewpoint of the camera, the received image is distorted by the topology of the scene and the albedo image to be expressed as [22], [41]:

\[ I_k^c(x^c, y^c) = \alpha(x^c, y^c)[A^c + B^c \cos(\phi(x^c, y^c) + 2\pi k/K)] + \alpha(x^c, y^c)\beta(x^c, y^c), \]  

where \(\alpha(x^c, y^c)\) represents the reflective parameter, \(\phi(x^c, y^c)\) represents the phase of the sine wave at camera coordinate \((x^c, y^c)\), \(\alpha(x^c, y^c)\beta(x^c, y^c)\) represents the image from ambient light with intensity \(\beta\), and the superscript, \(c\), signifies that this is the captured image.

If the projected sine pattern is shifted by a factor of \(2\pi/K\) for \(K \geq 3\) times, we obtain the phase \(\phi(x^c, y^c)\) by [22]:

\[ \phi(x^c, y^c) = \text{atan} \left[ \frac{\sum_{k=1}^{K} I_k^c(x^c, y^c) \sin(2\pi k/K)}{\sum_{k=1}^{K} I_k^c(x^c, y^c) \cos(2\pi k/K)} \right]. \]  

The wrapped phase is segmented based on the sine wave pattern peak-to-peak level for quality and is then unwrapped using the Goldstein Branch Cut algorithm [42]. And once the value of \(\phi\) is obtained, the accurate 3-D “depth” information, \((x^w, y^w, z^w)\), of a point can be calculated from \((x^c, y^c, \phi(x^c, y^c))\) as described in [22]. Surface noise spikes are removed using a 3 by 3 median filter. The surface color and reflectance does not affect the depth information [22]. A fingerprint with depth information is shown in Fig. 3 (b) - (d). As shown in Fig. 3 (d), the detailed 3-D geometry of ridges and valleys is clearly obtained. The scaled albedo image [23] can be written as:

\[ A(x^c, y^c) = \frac{1}{K} \sum_{k=1}^{K} I_k^c(x^c, y^c) = (A^c + \beta(x^c, y^c))\alpha(x^c, y^c), \]  

where \(A^c\) is a constant related to ambient light, \(\beta(x^c, y^c)\) is related to the camera/projector optics and optical path distances. We refer to \(A(x^c, y^c)\) as the ”albedo information” where as \(\alpha(x^c, y^c)\) is the true albedo of the surface. A fingerprint with albedo information is shown in Fig. 3 (a).

III. 3-D FINGERPRINT DEPTH FLATTENING

Although it is generally true that human fingers can be approximated by cylinders, the best-fit cylinder model can hardly capture the size variability in both horizontal and vertical directions. Hence, instead of using the parametric method to fit a cylinder to the 3-D surface, we improve the parametric approach by allowing different sized circles to be fit along the vertical direction (i.e. the direction along the length of the fingers), which will together form a tube adhering to the 3-D fingerprint. And because the detailed 3-D information is known, when unwrapping the circles, the Points Per Inch (PPI) value is controlled to preserve the local distances and defuse the distortion caused by flattening.

A. Single circle fitting

To form a tube fit to the 3-D surface, we first present a spring based method to fit a single circle to a 2-D set of points \(x_n^w, y_n^w\) for \(n = 1, 2, ..., N\). The spring based fit circle is shown in Figure 5. We chose the spring based method because our group has had considerable experience with this, but Least Squares methods [43] may also be used in the flattening process. There are two coordinate systems, (i) the image coordinates \(x^c, y^c\) which correspond to the column and row coordinate position and (ii) the world coordinate system

![Fig. 3. A 3-D fingerprint scan. (a) A 3-D finger with texture (surface reflectance variations or albedo image). (b) The 3-D fingerprint with depth rendering. (c) The cropped 3-D fingerprint. (d) The rotated crop.](image)
x^w, y^w, z^w. We choose a row y^c to fit the circle. The average world coordinate of that row determines y^{w,c}. The set of points, x^w_n, y^w_n, have both radial and angular noise and may be a partial arc segment or span the entire circumference of a circle. We first estimate a starting center point, (x^{w,c}, y^{w,c}, z^{w,c})

then find the average radius, r_{ave}, to the points.

B. Circle fit algorithm

![Diagram of circle fit algorithm]

For each point, we determine the distances
\[ \delta x_n = x^w_n - x^{w,c}, \]  
and
\[ \delta z_n = z^w_n - z^{w,c} \]

and the angle
\[ \theta_n = \arctan(\delta z_n, \delta x_n). \]

The distance from the center of the disc to the nth point is
\[ r_n = \sqrt{\delta x^2_n + \delta z^2_n}, \]  
and the average radius is then
\[ r_{ave} = \frac{1}{N} \sum_{n=1}^{N} r_n, \]  
with a distance difference for each point of
\[ \delta r_n = r_n - r_{ave}. \]

The distance difference is used to iteratively step the component values toward the final circle center. This can be a long process, if it is over dampened. So to prevent over damping, we constrain the value of Eq. (12) to be
\[ \delta r_n = \begin{cases} 
\frac{\delta r_n}{|\delta r_n|} & \text{for } |\delta r_n| \geq \delta r_{min} \\
\frac{\delta r_n}{|\delta r_n|} & \text{for } |\delta r_n| < \delta r_{min} 
\end{cases}, \]

where \(\delta r_{min}\) is a constant set by experience.

We map the polarity of the spring force as being in tension or compression by an angle such that
\[ \phi_n = \begin{cases} 
0 & \text{for } \delta r_n \geq 0 \\
\pi & \text{for } \delta r_n < 0 
\end{cases}, \]

and the X and Z components are then
\[ \delta x_n^c = |\delta r_n| \cos(\theta_n + \phi_n), \]
\[ \delta z_n^c = |\delta r_n| \sin(\theta_n + \phi_n). \]

Normally, there is a damping force along with the spring force to either prevent oscillation or amplify correction.

If we let the previous spring center be \(x^{w,cb4} = x^{w,c}, z^{w,cb4} = z^{w,c}\) then the new spring center is damped by
\[ x^{w,c} = x^{w,cb4} + \frac{\alpha_0}{N} \sum_{n=1}^{N} \delta x_n^c, \]
\[ z^{w,c} = z^{w,cb4} + \frac{\alpha_0}{N} \sum_{n=1}^{N} \delta z_n^c. \]

The process, starting at Eq. (8), is then repeated until a fixed number of iterations or the center point \(x^{w,c}, z^{w,c}\) converges by a change in polarity of \(\delta r_n\). There can be situations where the process is under damped and appears to converge because of oscillations in position, so to prevent this false convergence, we impose a minimum number of iterations. Fig. 4 shows an example of the ring fitting algorithm.
C. Multi-circle tube fitting

Now that we have defined how to fit a single circle to the fingerprint, the ring fitting process can be extended to form a tube by applying the single ring fitting to all positions along the surface in the $y^c$ direction. It is assumed that the surface is cropped and holes filled such that there is only one contiguous surface. The top and bottom row locations are determined to contain a minimum number of points to fit each ring to. At each $y^c$ row, between the top and bottom limits, a single ring is fit. For each ring, the first calculation is to determine an average $y^{w,c}$. From that coordinate, the circle fitting is applied to determine $x^{w,c}$ and $z^{w,c}$. Repeating this process from the top to bottom of the surface scan, an array of 3-Dimensional center points are determined.

The outliers of the ring center coordinates are removed by a 27 point median filter. Second order parametric equations are then fit to the center coordinates to affectively smooth the center points. From these smoothed center points, new rings are determined by averaging the radii to each associated surface point. The resulting array of radii are then also smoothed to complete the tube as shown in Fig. 6. Due to the variation of radii and center points of single circles, the tube in Fig. 6 is not a cylinder and is a better fit to the 3-D fingerprint.

The parametric equations for the center line world coordinates used in Fig. 6 are a function of the camera coordinates such that

$$
x^{w,c} = \alpha_{x,0}(y^c)^2 + \alpha_{x,1}y^c + \alpha_{x,2},
$$

$$
z^{w,c} = \alpha_{z,0}(y^c)^2 + \alpha_{z,1}y^c + \alpha_{z,2},
$$

For each center location and camera coordinate in Eq. (19), the average radius is found. The resulting array of radii are then smoothed using a moving average process.

D. Level 1 flattening algorithm

Once the tube center points are known, the surface points are flattened by calculating the arc distance to each as shown in Fig. 7. The arc based distance is used as the new $x^w$ coordinate of the point. The radial difference between a specific point and from the ring radius becomes its new $z^w$ coordinate, and it keeps its original $y^w$ coordinate. The 3-Dimensional results are shown in Fig. 8 where the left image is the top view (i.e., Z axis is perpendicular to the page) of the level 1 flattening and the right two images are angle and edge views (i.e., Y axis is perpendicular to page) showing the residual warping.

E. Flattening

The warping in level 1 flattening can be removed by several methods. The springs method may be used to preserve distances between ridges. However, if the level 1 warping is not extreme, the surface may be fit with a mean valued surface. The difference between the level 1 and the mean valued surface becomes the level 2 flattened surface. To estimate the mean surface height we use a trend filter that fits a sliding or “moving” plane across the surface where the smoothed value is the center height of the plane. The idea is to choose the
Fig. 9. The 2-D equivalent flattened fingerprint employing the depth information.

plane (i.e., kernel size) length and width to be greater than the ridge widths so the resulting mean valued surface contains minimal ridge artifacts but at the same time is small enough to follow the surface half way between the ridge peaks and valleys. If it were the case that the curvature is extreme, a measure of curvature such as the fractal dimension [44] may be employed to indicate the level of curvature and determine if a simple smoothing filter or a more complicated springs type algorithm should be used as level 2 flattening. We did not experience this problem with our data set so we only used the smoothing filter method.

Figure 9 shows a binary result where black is above the mean values and white is below. Note that the width of the white and black ridge components are about equal. In Fig. 9, most of the ridges are clearly shown though ridges near the edge become blurry and hard to be identified which is mainly caused by the poor quality in outer area of the 3-D depth information. Although it is impossible to flatten the 3-D surface to a 2-D plane without introducing some distortion, the distortion is minimized by variation of the diameters and controlling the PPI value. The final uniformly spaced PPI data is achieved by mapping backwards to the flattened point cloud data. Each of the uniformly spaced points will be mapped in between four adjacent points in the flattened point cloud so the values are determined by bilinear interpolation between these surrounding points.

IV. FUSING FLATTENED 2-D FINGERPRINTS

Figure 10 shows a 3-D fingerprint obtained by the scanner where ridge depth is clear at the center portion of scan. But the print becomes noisy near the edges. The albedo component image tends to be lower quality but more uniform in quality from the center out to the edges. We hypothesize two sources of depth corruption. One source may be the scan time of 0.7 seconds which makes the scan vulnerable to finger motion. Motion would corrupt the high gradient sides more for the depth measurement than the albedo component image which is only sensitive to lateral motion. The second hypothesis is that the depth measurement requires both the projector and the camera light paths while the albedo component would only be corrupted by blurring in the camera path.

Now because both depth and albedo information are available in PMP scanning, an alternative way to achieve 2-D equivalent fingerprints could be to extract ridges by exploiting albedo. Figure 11 shows an example albedo image used to obtain ridge information along with the 2-D scan derived by mapping this albedo image onto the flattened print. Noticing that depth flattened fingerprints do not achieve high scan local quality in areas of low SNR (edges) and that ridge detail is clear in the albedo image for these same regions, we propose a novel fusion of depth and albedo prints in order to maximize scan quality at all visible portions of the finger.

Fig. 10. A 3-D fingerprint scan. (a) A 3-D fingerprint with depth rendering. (b) Cropped and rotated center part of the 3-D fingerprint. (c) Cropped and rotated edge part of the 3-D fingerprint. (d) The depth flattened 3-D fingerprint. In squared area, albedo flattened fingerprint outperforms depth one.

Fig. 11. (a) An albedo image. (b) The albedo flattened 3-D fingerprint. In squared area, depth flattened fingerprint outperforms albedo one.

Because the albedo print is derived from the component PMP images used to form the depth print. Ridges from these two are well aligned as shown in Fig. 12. As such, we can fuse these two data sets to achieve a single fingerprint that exceeds either of the two prior in quality. The simplest approach is by selecting sub-blocks with higher local quality from the two fingerprints in mutually exclusive fashion. In order to assess quality, we rely upon NIST Fingerprint Image Software (NFIS).

The NFIS is a public domain source code distribution organized into seven major packages [5]. One of them is Minutiae Detection System (MINDTCT), which divides the image into a grid of blocks, $8 \times 8$ points in each block under 500 PPI, and assesses the quality of each block by computing the flow map, low contrast map, low flow map, and high
Fig. 12. A combined 3-D fingerprint where depth ridges are aligned well with albedo ridges.

curvature map.

Fig. 13. Different maps created to assess the local quality [5]. The white cross marks, squared out, in the images label blocks with sufficiently low contrast, low flow, or high curve. (a) Input fingerprint. (b) Low contrast map. (c) Low flow map. (d) High curve map.

Figure 13 gives an example to illustrate how the different maps are created by NFIS. The map in Fig. 13 (b) is called the low contrast map which is computed where blocks of sufficiently low contrast are flagged. This map separates the background of the image from the fingerprint. One way to distinguish a low contrast block from a block containing well-defined ridge, is to compare their pixel intensity distributions. By definition, there is little dynamic range in pixel intensity in a low contrast area, so the distribution of pixel intensities will be very narrow. It is possible, when trying to derive the ridge flow direction, for some blocks to have no dominant ridge flow. These blocks typically correspond to low-quality and blurry areas in the image, and are marked as low flow area shown in Fig. 13 (c). Another part of fingerprint image that is problematic is in areas of high curvature, especially the core and delta regions of a fingerprint [12]. The high curve map marks blocks that are in high-curvature areas of the fingerprint as shown in Fig. 13 (d). A detailed implementation along with the mathematical models for these maps is presented in [5].

Fig. 14. Quality maps and fused result. The white blocks represent the highest quality, whereas the black blocks represent the background. (a) Local quality map of depth flattened fingerprint. (b) Local quality map of albedo flattened fingerprint. (c) Local quality map of fused flattened fingerprint. (d) The fused flattened fingerprint.

The information in these maps is integrated into one general map which contains 5 levels of quality with 4 being the highest and 0 the lowest in such a way [5]:

1) 0 is assigned to low contrast area;
2) 1 and 2 are assigned to low flow and high curve area;
3) 3 is assigned to low flow and high curve neighbor area;
4) 4 is good quality without any of above.

Since not only does the local quality map mark the low quality area but also it labels the high curve area that may cause incorrect match between fingerprints [5], it is ideal for us to assess the qualities of albedo and depth flattened fingerprints. And fuse these two based on the local quality maps. Even if the fusion may result the clear area (with high curve) blurred, it still promotes a higher match performance which is the ultimate objective of fingerprint.

To visualize the quality map, we transform the local quality map back to the image size as shown in Fig. 14. The best local quality zone, zone 4, corresponds to white block, while the worst quality zones, generally background, are black blocks. Where the local quality of the albedo block is higher than the depth block, we replace the depth block with the albedo block. The fused result is shown in Fig. 14 (c) and (d), where the low quality zones are mainly caused by the high curvature, not low flow or low contrast anymore.

The depth and albedo fusion method is basically an image tiling method so there was concern about abrupt pixel value changes correlating to the tile boundaries. In particular, there was a concern of false feature generation along the tile boundaries between albedo and depth tiles. If these boundaries occurred in the same location in different scans, there would be the possibility of skewing the matching in favor of the fused prints. To evaluate this possible problem, we manually inspected the scans and looked for visible boundaries. We also looked at a sample of the scans with minutiae and line endings marked. Our conclusion was that there was no visible
correlation because the albedo and depth are accurately encoded to the same corresponding pixel locations, and because there are optical similarities in the binarized albedo and depth ridge patterns. Furthermore, the finger positions between scans changed enough to have different tile boundary locations. The edge differences that did exist acted like noise and were limited to less than single ridge widths and to only the block edges which comprise a significantly small number of pixels within the entire print region.

V. RESULTS

In this study, a fingerprint database consisted of 441 3-D fingerprints from 11 subjects. All fingers were scanned by using the SLI 3-D fingerprint scanner provided by Flashscan3D, LLC. All the 3-D fingerprints were flattened by using the fit tube algorithm into both depth and albedo flattened 2-D equivalent fingerprints, and the PPI was controlled to 500. The flattened depth and albedo fingerprints were further fused by means of the local quality based fusion described in Sec. IV.

We used the gray level form of the albedo and depth encoded prints for determining quality but used binary for the matching performance analysis. The reasons we used binary images in the matching was because of the inherent differences between contact versus non-contact gray level images. In contact print images, the regions between contacting ridges is blank and void of features whereas in non-contact imagery there is texture everywhere. Our goal in this research is to establish the utility of depth information so by using the binary form of the prints, we reduce the dimensionality and complexity of the problem to get a clearer result.

A. Comparing between ink rolled and flattened fingerprints

To demonstrate the visual compatibility of the flattened prints and 2-D ink rolled prints, we have collected a 2-D ink rolled fingerprints database with 150 prints from 150 different fingers. The 2-D prints were collected by a trained operator, where the 2-D database is smaller than our 3-D database. Two typical examples are shown in Fig. 15. Note that for both depth and albedo flattened prints, the flattening of the 3-D surface is based on the same shape information, whereas only the ridges information is different. Thus, these two kinds of flattened fingerprints would be aligned well except that the clarity of ridges is different, and their alignment with 2D ink rolled prints would also be the same.

As shown in Fig. 15, for the same finger, either depth or albedo flattened 3-D fingerprint is aligned well with the 2-D ink rolled fingerprint. Most of the ridges are connected correctly from the ink rolled to the flattened, although it is true that some ridges are mis-aligned. The mis-alignment is caused by many possible reasons. And, an important reason is the skin deformation created when collecting the 2-D ink rolled fingerprints. In the mis-alignment area, the distance between ridges of 2-D fingerprints is either bigger or smaller than the average distance. This high variance of distance indicates skin deformation in that area while rolling the finger on paper.

Minutiae points are widely used for fingerprint verification [12], [45]. The MINDTCT system takes a fingerprint image and locates all the minutiae in the image, assigning to each minutiae point its location, orientation, type, and quality. It also calculates the quality and reliability of the minutiae detected which ranges from 0 to 1 [5]. Generally, the minutiae with quality greater than 0.75 are regarded as high quality minutiae. Tabassi et al have observed that, generally, if a fingerprint has more than 20 of these high quality minutiae, it would be more likely to identify correctly by fingerprint recognition systems. Thus, two comparisons between 2-D ink rolled and flattened 3-D fingerprints are presented in Fig. 16, and the minutiae, detected by MINDTCT, with quality greater than 0.75 are marked out. The false detected minutiae are squared out. Admittedly, there are false minutiae existing in both ink rolled and flattened, but 2-D ink rolled fingerprints suffer the difficulty to get ridges in the indentation areas. In 2-D ink rolled fingerprints, ridges’ discontinuity is noticeable because of the surface indentations obstructing surface contact and thus occluding the ridge prints. But in flattened 3-D fingerprints, these indentations are flattened away to reveal the continuous ridges inside the indentations.

B. Quality analysis

The 2-D ink rolled, depth, albedo and fused fingerprint data sets were run through the NIST software to measure the statistical values. The percentage of blocks in quality zone 4 (the best local quality), the percentages of overall quality
numbers, and the number of minutiae with quality greater than 0.75 are selected as reliable quality evaluations for the data sets. By segmenting the images into blocks with $8 \times 8$ points in each block, NIST assigns each block with a local quality zone value. The percentage of blocks in quality zone 1, 2, 3 and 4 are given in Fig. 17 with 4 representing the best local quality and 1 the worst. The comparison illustrates that the fused fingerprints have the highest percentage of blocks with the best local quality.

Besides the local quality zone value, NIST further gives each fingerprint the overall quality number, with 1 representing the highest quality and 5 the worst. Experiments show that the ink rolled fingerprint data set achieves the best average quality number of 2.65, where the fused, depth and albedo fingerprints give 2.93, 4.18 and 2.94 respectively. However, from the Fig. 18, it is clear that the fused fingerprint data set has a higher percentage of best two quality numbers, quality number 1 and quality number 2, than ink rolled, depth and albedo fingerprint data sets.

From [37], the average number of minutiae with quality greater than 0.75 ($\text{min75}$) can be used for performance evaluation. We can conclude from Fig. 19 that our final fused results have an average 70.84 minutiae with high quality which is higher than 41.09, 56.65 and 51.65 respectively from ink rolled, depth and albedo sets. Based on Tabassi’s observation [5] that fingerprints with high number of min75 ($> 20$) were more likely to be identified correctly, our fused fingerprints have enough min75 for verification.
C. Fingerprint verification

The matching performances of depth, albedo and fused fingerprint data sets are studied. In NIST software package, BOZORTH3 is offered as the automatic fingerprint matching algorithm. It employs feature detection to find the minutiae of the fingerprints and produces a real valued similarity score. The higher the score is, the more likelihood that the two fingers are from the same finger of the same subject.

We note the output value as genuine score [6] if the input two fingerprints are actually from the same finger of the same subject, whereas impostor score [6] if the two fingerprints are from the same finger but of different subjects. For each pair of two fingerprints that are from the same finger of the same subject, we obtain one genuine score. There are 1,011 genuine scores. Correspondingly, each fingerprint is matched with other fingerprints (the same finger of different subjects) where the other fingerprints are randomly selected. There are 1,011 impostor scores.

Figure 20 shows the distribution of genuine and impostor scores for depth, albedo, and fused fingerprint data sets. As we can expect, the higher the performance of the data set is, the less overlapping the genuine and impostor scores will be. In Fig. 20, the genuine score (solid lines) and impostor score (dashed lines) are shown for the three sets where the fused data set achieves the clearest distinction between genuine and impostor pairs.

Further, based on the distributions, we give the Receiver Operating Characteristic (ROC) which is a statement of the performance of the fingerprint verification system [6], [12], [46]–[48] in Fig. 21. To evaluate the performance, we have to set the operating threshold. For each threshold, we compute out the False Accept Rate (FAR) and True Accept Rate (TAR). For a generally specific FAR 0.01, the TAR of the fused data set is 0.98, while the TAR of the depth and albedo are 0.93 and 0.96. The fused set outperforms the depth and albedo sets in ROC.

VI. CONCLUSION

In this paper, we present a data acquisition and processing procedure for 3-D fingerprints, which includes obtaining 3-D fingerprints, flattening of 3-D fingerprints into 2-D depth and albedo fingerprints, and fusing of the two flattened fingerprints. In order to obtain the 3-D fingerprints, PMP is employed due to its high precision with only a few patterns. In the flattening algorithm, we fit a deformable tube consisting of multiple circles to flatten the 3-D fingerprints. And by “unrolling” the tube and controlling the PPI value, the distortion caused by flattening is defused. Thus, we obtain the depth flattened fingerprint with the ridge information from the world coordinates (or depth) of each point. Furthermore, we obtain the albedo flattened 3-D fingerprint by substituting the albedo for the ridge information. Results show that both depth and albedo flattened fingerprints are visually similar to the 2-D ink rolled fingerprints. However, there was enough difference in spatial distortion between the ink rolled prints and the 3-D flattened ones to corrupt cross matching between the two data sets.

Detailed experimental results of flattened 3-D fingerprints using a quality based fusion method are given and discussed.
in Sec. V, which indicate a high performance and robustness of the flattening and fusing procedures. Most significantly, the results show that the fused prints have higher matching performance than albedo only or depth only prints. However, by exclusively selecting either albedo or depth blocks, we exclude a considerable amount of information. For future research, the albedo and depth blocks could be mathematically combined to achieve a higher performance. Future work would also include testing with a larger database, interoperability [46] between 3-D and 2-D fingerprints, and employment of multiple cameras [49], to obtain more surrounding information and higher depth precision of 3-D fingerprints.

REFERENCES


Yongchang Wang received his BEng degree in Electrical Engineering in 2005 from Zhejiang University, Hangzhou (China) and his MS and PhD degrees in Electrical Engineering respectively in 2008 and 2010 from the University of Kentucky. Yongchang’s principal research interests is in the area of 3-D scanning by means of structured light for applications including biometrics and computer vision. His work in 3-D fingerprint scanning has been recognized by several on-line news magazines including the Technology Review, published by MIT, and by the SPIE Newsroom. He has 8 technical papers published in the areas of 3-D scanning and 3-D fingerprinting. Yongchang is presently a signal and image processing engineer for KLA-Tencor, in Milpitas, CA.

Laurence G. Hassebrook is a Blazie Professor of Electrical and Computer Engineering, a Professional Engineer and an active member of the Center for Visualization and Virtual Environments at University of Kentucky. While studying at the Center of Excellence in Optical Processing, he received his Ph.D. degree from Carnegie Mellon University in 1990, his M.S.E.E. from Syracuse University in 1987 and his B.S.E.E. from University of Nebraska in Lincoln, in 1979. He worked at IBM Endicott, New York between 1981 through 1987. His research interests are in 3-Dimensional Data Acquisition, pattern recognition and N-Dimensional signal processing. Current work includes 3-D surface scanning of objects in motion, dynamic pattern projection for multi-target tracking, automatic target recognition, and scene reconstruction from partial images. Dr. Hassebrook has published more than 124 technical papers.

Dr. Daniel Lau received his B.Sc. degree (with highest distinction) in Electrical Engineering from Purdue University, West Lafayette, IN, in 1995 and the Ph.D. degree from the University of Delaware, Newark, in 1999. Today, he is an Associate Professor at the University of Kentucky, Lexington. Prior to these appointments, Dr. Lau was a DSP Engineering at Aware, Inc., and an Image and Signal Processing Engineer at Lawrence Livermore National Laboratory. Among his many published works is an article in the Proceedings of the IEEE and his own book, Modern Digital Halftoning, now in its second edition and published by CRC Press. His research interests include 3-D imaging sensors, 3-D fingerprint identification, and multispectral color acquisition and display. Daniel’s work has also been featured in such trade magazines as Vision Systems Design, Photonics Spectra, Imaging Insights, and Prosilica Camera News.