Forensic Print Extraction Using 3-D Technology and its Processing

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ABSTRACT

Biometric evidence plays a crucial role in criminal scene analysis. Forensic prints can be extracted from any solid surface such as firearms, doorknobs, carpets and mugs. Prints such as fingerprints, palm prints, footprints and lip-prints can be classified into patent, latent, and three-dimensional plastic prints. Traditionally, law enforcement officers capture these forensic traits using an electronic device or extract them manually, and save the data electronically using special scanners. The reliability and accuracy of the method depends on the ability of the officer or the electronic device to extract and analyze the data. Furthermore, the 2-D acquisition and processing system is laborious and cumbersome. This can lead to the increase in false positive and true negative rates in print matching. In this paper, a method and system to extract forensic prints from any surface, irrespective of its shape, is presented. First, a suitable 3-D camera is used to capture images of the forensic print, and then the 3-D image is processed and unwrapped to obtain 2-D equivalent biometric prints. Computer simulations demonstrate the effectiveness of using 3-D technology for biometric matching of fingerprints, palm prints, and lip-prints. This system can be further extended to other biometric and non-biometric modalities.

Keywords: Forensic, biometric, fingerprint, palmprint, lip-print, unrolling, modeling, 3-D, 2-D

1. INTRODUCTION

Forensic science is defined as the body of scientific knowledge and technical methods used to investigate and construe evidences, to provide valuable insight in criminal, civil and administrative proceedings. It focuses on the demonstration of the existence and the investigation of an offence, on the individualization of a perpetrator and on the description of a modus operandi. The process of forensic identification can be performed with (i) personal data, (ii) personal belongings such as keys, tags, laptops, and (iii) biometric traits[1, 2].

Biometric recognition is an automated process used for the recognition of human beings by measuring and analyzing their distinctive physiological and behavioral characteristics. The process consists of extracting and matching biometric features from a reference and a test sample, followed by computing a score representing a distance or a similarity between the two samples. The recognition algorithms can be applied to a variety of scenarios including forensic investigations, commercial application such as US-VISIT's IDENT program, the FBI's NGI (formerly IAFIS) service [3], passports, civilian identification cards, access control, and bio-cryptography [4-7]. Most biometric traits are unique, universal, measurable, and permanent [8]. Some of the common biometric features that can be captured from a forensic scene are fingerprints, palm-prints, lip-prints, hand prints, foot prints, and boot prints. A sample obtained at the crime scene is called as the crime scene sample, forensic print or trace or unknown item. Biometric recognition assist forensic investigation in two distinct ways: 1) as an instrument to assist in investigation and (ii) as evidence in a court of law [2].

Identification, individualization, and association are three significant forensic interpretations required in an investigation. Identification provides the identity of a person, individualization is a report of the evidential value of a trace, in the light of a pair of mutually exclusive hypotheses related to the source of this trace [9]. Association involves linking and selecting individuals, groups, objects, and events [10]. There are two main purposes for forensic identification of humans: suspect identification and victim identification. Evidence such as fingerprints, palm-prints, foot-prints, bite marks, and blood samples are collected at crime scenes to prove the guilt or innocence of the suspects. The goal of victim identification is

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to determine the identity of victims based on characteristics of the human remains. Forensic-Biometric technology can also be used for the identification of missing persons or John Doe's from a mass disaster.

Forensic prints can be classified as patent, latent, and three-dimensional plastic prints. Latent prints are invisible to the naked eye and are formed due to the sweat and oil on the skin's surface. Patent prints are visible to the naked eye and are formed on blood, grease, dye or dirt. Three-dimensional plastic prints are formed when the individual presses wax, soap, fresh paint or fresh cement [11]. Prints such as fingerprints, hand prints, and lip marks are traditionally captured using physical means, whereas face, voice, and DNA are captured using digital means. The stability of certain biometric traits such as fingerprint, palm-print are permanent (i.e. they do not change), while face and voice are not permanent. They change over time and emotion. Physical traces are preferred over digital traces due to its distinctiveness, however, there are new technologies capable of capturing these physical traits by digital means. Traditionally, forensic prints are collected from a crime scene by experts proficient in forensic science techniques to reveal or extract fingerprints from surfaces and objects using chemical or physical methods. The traces can then be photographed, marked up for distinctive features by skilled examiners. The reliability and accuracy of the method depends on the ability of the officer or the electronic device to extract and analyze the data. Furthermore, the 2-D acquisition and processing system is laborious and cumbersome. This can lead to the increase in false positive and true negative rates in print matching.[2]

Fingerprints consists of friction ridge patterns. These ridges and valleys produce precise details of formations known as minutiae. Bifurcation, ridge ending, island, delta, pore, and trifurcation are few of the well-known minutiae in fingerprints [12, 13]. These features are used to search an automated fingerprint identification system (AFIS) [11]. The main identifiers used in palm-print recognition system are hand geometrical features such as finger width, length and thickness, and principal lines or flexion creases, secondary creases or wrinkles, and ridges. Lip prints/marks are another common forensic evidence available at the crime scene[14]. Lips have wrinkles and grooves on labial mucosa, known as sulci labiorum that form characteristic and unique patterns. Like fingerprints and palmprints, lip prints are unique and permanent. Minor trauma such as inflammations do not change the patterns, however major trauma that may lead to scaring and surgeries can change the characteristics. Surgeries and treatments that alter the shape and size of the lips alter the patterns[15, 16]

One of the most challenging problems in forensic-biometric recognition is the erroneous matching of forensic prints with the database. This may occur because 1) the extracted prints are not viable for verification, and 2) the prints have poor image quality and significant amount of distortions. Consequently, the overall performance of a recognition technology is principally influenced by the quality of the extracted forensic print and environmental conditions. Although these factors are common in most biometric applications, forensic processes tend to exploit their unpredictability [2].

The past few years have seen a spike in interest in 3-D imaging and forensics. A 3-D scanner can capture texture of the surface and the depth information. This results in more number of features captured per image. Some of the advantages of 3-D imaging devices are 1) It generates higher image quality, resulting in the improvement of matching rates, 2) It generates distortion-free images are achieved as dry skin, sweat, oil, etc. do not affect a touchless interface, 3) It can capture partial/-scarred prints more effectively, and 4) Other geometric constraints can be determined such as volume, detailed friction ridge information, and thickness.[14, 17] Over the years, several 3-D acquisition algorithms have been developed such as structured light, stereo, and structure from motion. Each technique has it pros and cons and it's up to the technician to choose the ideal 3-D scanner based on the environment and circumstances. The creation of a new database format results in the problem of inter-operability between database and agencies. There is growing recognition of the need for biometric print interoperability [18], and an inter-operable match may result in erroneous results.

There is a reasonable volume of literature on unrolling or converting 3-D fingerprint images to equivalent 2-D fingerprint images. [19-24]. The techniques can generally be classified into parametric and non-parametric unrolling algorithms. While parametric techniques assume a shape of the 3-D image to be a sphere [21, 24], tube [21-23] or cylinder [19, 21], non-parametric techniques strive to preserve the geodesic distances [19]. Wang et al. developed a parametric approach to model 3-D fingerprint images using the fit sphere unwrapping algorithm [23]. Chen et al. modeled the images by using a 3-D cylindrical parametric approach. Abramovich et al. unrolled the 3-D images into 2-D images by circular approximation of the cross sections of the finger [22]. A non-parametric approach proposed by Chen et al. divides the 3-D image into thin slices and unrolls each slice to minimize stretching effect. Fatehpuria et al. incorporated the Springs algorithm' to unroll the images. Shafaei et al. improved this approach by using curvature analysis to detect ridges and valleys [25]. Most of the state of art methods are developed for 3-D fingerprint images and cannot be utilized for other biometric traits.

Furthermore, these methods were developed assuming the biometric trait has minimum deformations. Rajeev et al. developed a non-parametric method to unroll post-mortem fingerprints by utilizing the Euclidean distance approach [17].

This paper proposes to use a 3-D sensor and processing module to improve acquisition, extract forensic prints from surfaces of varying depth, unroll the 3-D prints to equivalent 2-D prints provide an inter-operability with 3-D and 2-D databases for modalities such as fingerprints, palmprints, and lip-prints. The rest of this paper is organized as follows: the proposed system is described in Section 2, and computer simulations and performances are given in Section 3. Finally, conclusions and future works are drawn in Section 4.

2. PROPOSED SYSTEM

The proposed biometric forensic system captures a 3-D image of the forensic print, pre-processes it and unrolls it to make it viable for automated recognition. The following sections provides a wider description of this process. Figure 1 shows the operation flow of the proposed system.

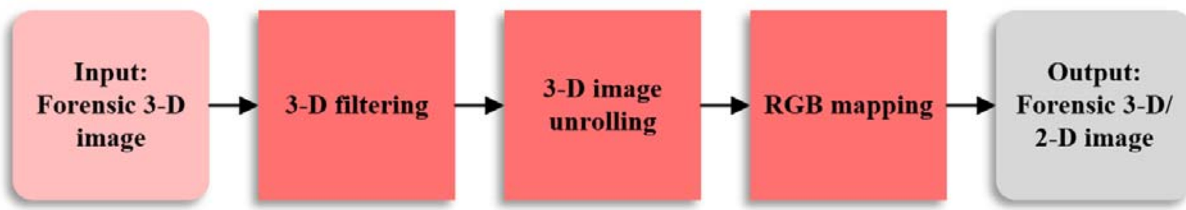

Figure 1: Flow diagram of the proposed forensic print unrolling method

2.1 3-D image acquisition, extraction and filtering

When the forensic prints are revealed by forensic science experts using chemical methods, the prints should be captured using portable high quality 3-D cameras. Images must be captured such that it includes minimum background information. Once captured, the image files are transferred onto a device with processing capabilities. The 3-D co-ordinates and the RGB image are extracted. The quality of the 3-D image is crucial for successful processing and it is dependent on factors such as illumination, environment, camera, and 3-D reconstruction technique. Consequently, a pre-processing segment is necessary to assure that the unrolled 3-D image can be used for biometric recognition. Erroneous points can be removed by performing block wise standard deviation filtering or alpha trim mean filtering [26]. The principle behind this approach is that erroneous features in a block have a larger deviation from the mean when compared to the object. These features are identified ad removed from the 3-D image. Figure 2 shows some of the input modalities used by the proposed system.

a b c

Figure 2: Sample 3-D images used in this paper. (a) 3-D fingerprint, (b) 3-D palm-print and (c) 3-D lip-print

2.2 3-D unrolling

A non-parametric approach is used to perform forensic print unrolling. This step involves selecting a starting point and then unrolling to the sides. The central region of the print is identified and the unrolling algorithm is applied towards the sides. A non-parametric approach is used to unroll the 3-D image. A compensation model is created, which is unique for every image. This model identifies all the holes in the 3-D image and determines the location of all the points along the hole. Equation 1 defines the compensation model. The unrolling procedure is not affected by the compensation model since it is a transient model. Although the holes can be filled using interpolation techniques, it is recommended to forego this step to avoid mismatches. Next, the 3-D image is unrolled slice by slice using Equation 2-Equation 3 if there is no abnormality, and Equation 4-Equation 5 if the compensation model recorded an abnormality.

$$\hat{P}(x,y,z)_{i,j} = \{P(x,y,z)_{i-1,j-1} \,\forall\, P(x,y,z)_{i,j} = NaN \,\forall\, x,y,z\}$$ Equation 1

$$D_{i,j} = Euclidean\{(x,z)_{i,j}, (x,z)_{i,j+1} \,\forall\, y, \forall\, x \neq 0 \}$$ Equation 2

$$x_{i,j+1} = concatenate\{x_{i,j}, d(i,j) \,\forall\, y, \forall\, x \neq 0 \}$$ Equation 3

$$D1_{i,j} = Euclidean\{(x,z)_{i,j-k}, (x,z)_{i,j+1} \,\forall\, y, \forall\, x = 0, x_{j-k} \neq 0 \}$$ Equation 4

$$x_{i,j+1} = concatenate\{x_{i,j-k}, D1(i,j) \,\forall\, y, \forall\, x = 0, x_{j-k} \neq 0 \}$$ Equation 5

Where, x, y, and z are the 3-D co-ordinates, D and D1 are the Euclidean distance, and P is the compensation model.

2.3 RGB mapping

Unlike generic 3-D biometric imaging, where the texture of the image provides the intricate friction ridge pattern, the texture on forensic latent prints cannot be relied upon. The texture of the surface may be rough or smooth as shown in Figure 3. However, the chemical and physical methods applied by the skilled technicians to reveal the features result in a pixel level feature on the 3-D surface. Therefore, the RGB values of each point in the input 3-D image are mapped onto the equivalent unrolled 2-D/3-D forensic print.

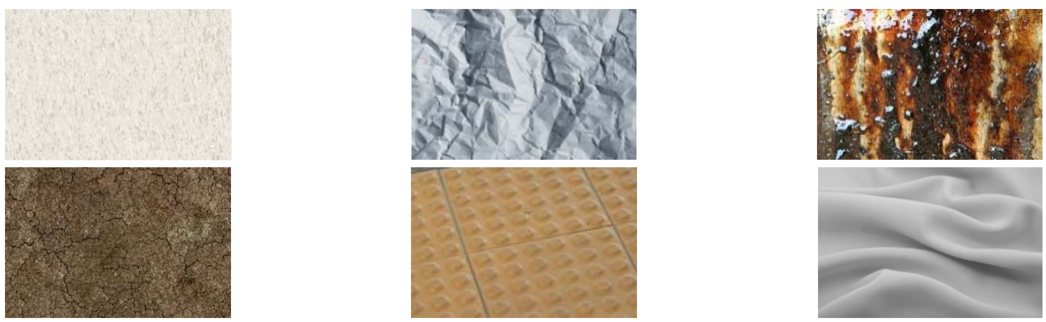

Figure 3: Different possible textures. From **top left-right**: smooth(marble), wrinkled, and greasy[27]; **bottom left-right:** cracked, bumpy, and silky. [28]

3. COMPUTER SIMULATIONS

The proposed 3-D forensic unrolling technique was simulated on fingerprints, palmprints and lip-prints. The following section describes the multi-modal database and the experimental results.

3.1 Database synthesis - Fingerprints

In order to benchmark the capability of the proposed forensic unrolling algorithm, it has to be tested on a versatile 3-D forensic database. However, due to the unavailability of such a database, the authors have synthesized a 3-D forensic database by fusing the texture from Describable Textures Dataset [28] with the RGB information of the images in the FVC 2004 fingerprint database [29]. The FVC2004 database consists of 4 datasets, which were acquired using different sensor types and each of them contains 8 impressions of 10 fingers.

The Describable Textures Dataset (DTD) is a collection of textural images [28]. It has 47 categories, 120 images for each category. For this paper, the textural image category was preferred. It was chosen because the textural pixel variations mimic the changes of depth on a 3-D surface. The images contain at least 90% of the surface representing the category attribute. These images were used to synthesize the depth of the surface of the print.

3.2 Database synthesis – Palmprints

The Tsinghua 500PPI Palmprint Database (THUPALMLAB) has 1280 palmprint images captured from 80 subjects. Each image has an original resolution of 2040x2040. The images were acquired using the Hisign scanner [30]. The texture images from the describable texture database were synthesized as depth onto the THUPALMLAB database. For the sake of genuineness, random images from the wrinkled texture folder were chosen to provide depth to the palm-prints.

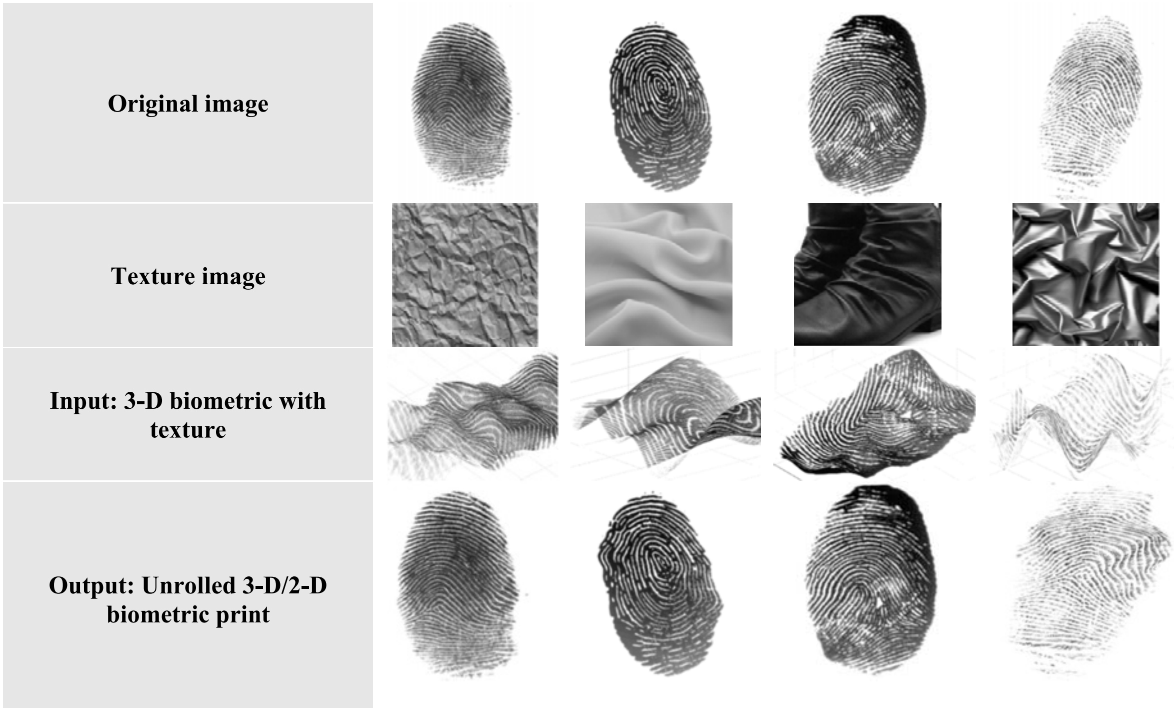

Figure 4: Shows the input image, texture image, the depth fused biometric image and the unrolled 3-D/2-D fingerprints.

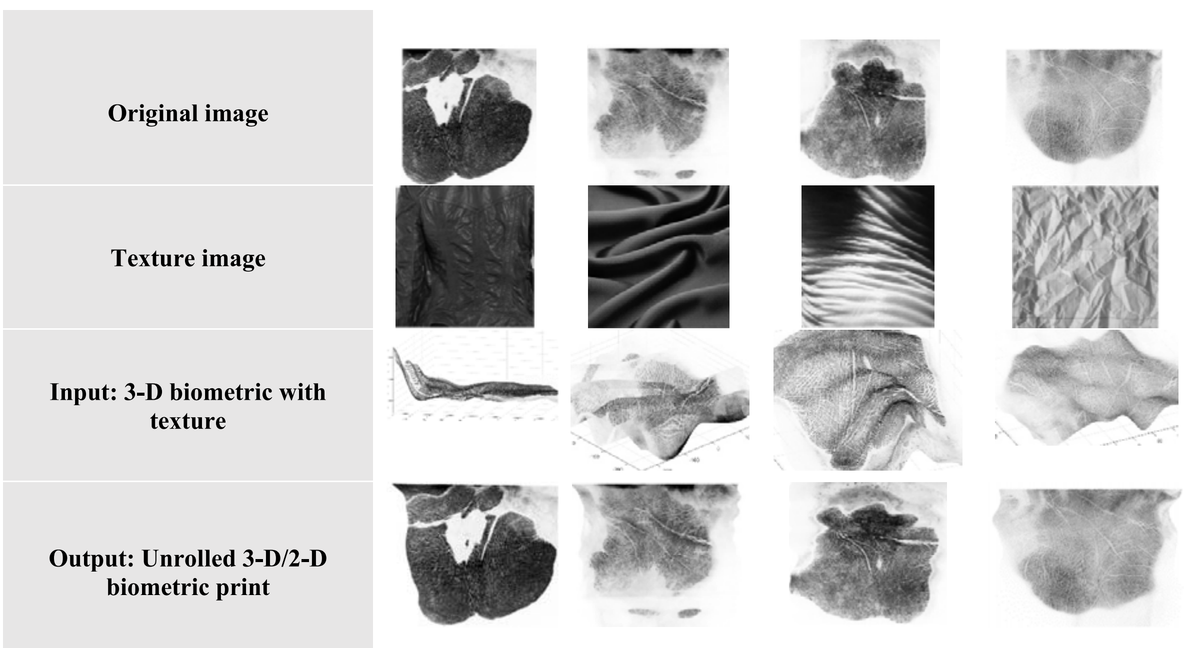

Figure 5: Shows the input image, texture image, the depth fused biometric image and the unrolled 3-D/2-D palm-prints.

3.3 Database synthesis – Lip prints

The lip-print database created by University of Silesia at Katowice contains 60 lip print samples taken from 15 subjects, 4 samples from each subject. The scans are 16 bit grayscale images with a resolution of 300dpi [6]. The texture images from the describable texture database were synthesized as depth onto the Lip print database. For the sake of genuineness, random images from the wrinkled texture folder were chosen to provide depth to the lip-prints.

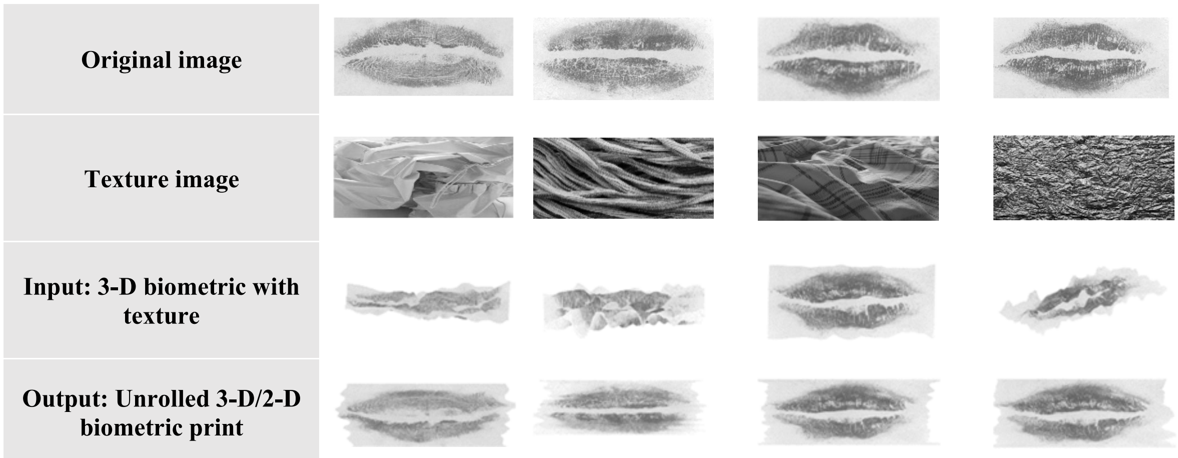

Figure 6: Shows the input image, texture image, the depth fused biometric image and the unrolled 3-D/2-D palm-prints.

Figure 4, Figure 5, and Figure 6 show the results of the database synthesis in the first three rows of each figure, and the last row of each figure shows the results of the unrolling algorithm. The algorithm causes few distortions and stretching effects when the depth variations are relatively high. The distorted images are still viable for manual feature extraction. For verification and identification purposes, these unrolled images can be further enhanced, filtered, and binarized with a AME/EME [31, 32]based feedback system to yield biometric quality images. Feature based matching algorithms that incorporate image features [26]with biometric features can be used to provide better recognition results.

Although the output images have clear color pixels, this may not always be the case. An actual 3-D forensic print may or may not have higher resolution and quality. This in turn may or may not produce results of higher quality and precision. Another approach to boost the performance of the software is to combine the features extracted automatically with the markups of different examiners.

4. CONCLUSION

Forensic science is an integral aspect in solving a criminal case or identifying a person in a mass disaster. This paper attempted to solve some of the most challenging problems in forensic-biometric science, namely, digital extraction of the forensic print and digital modeling of the print. The process involved (i) 3-D image filtering, (ii) 3-D image unrolling, and (iii) RGB mapping. An approach to unroll 3-D forensic prints to obtain 2-D rolled equivalent forensic prints images was proposed. A versatile 3-D multi-modal database was created by synthesizing the depth on each biometric modal database. The robustness of the method was tested by applying the algorithm on biometric 3-D modalities such as fingerprints, palmprints and lip-prints. The visual results show that the technique models the 3-D images back to the 2-D image with or without distortions, based on the amount of depth variability. Furthermore, the mapping algorithm can be applied to footprints, boot-prints, and hand prints. Future work includes creating a patent, latent, 2-D and 3-D multi-modal database for further study. There is also room for improvement in the recognition algorithms to recognize, convert and match images of different formats.

REFERENCES

[1] A. Pfitzmann, “Biometrie–wie einsetzen und wie keinesfalls?,” Informatik-Spektrum, 29(5), 353-356 (2006).

[2] A. K. Jain, and A. Ross, “Bridging the gap: from biometrics to forensics,” Phil. Trans. R. Soc. B, 370(1674), 20140254 (2015).

[3] S. Bakhtiari, S. S. Agaian, and M. Jamshidi, "Local fingerprint image reconstruction based on gabor filtering." 840602-840602-11 (2012).

[4] S. Wang, and J. Hu, “Alignment-free cancelable fingerprint template design: A densely infinite-to-one mapping (DITOM) approach,” Pattern Recognition, 45(12), 4129-4137 (2012).

[5] "Biometric Standards Requirements for US-VISIT", http://www.dhs.gov/usvisit, (2010).

[6] "Home - Biometrics Research at University of Silesia", http://biometrics.us.edu.pl/, (2017).

[7] W. Zhou, J. Hu, I. Petersen et al., "Performance evaluation of 2D to 3D fingerprint recognition." 3, 1736-1741 (2013).

[8] K. Sauerwein, T. B. Saul, D. W. Steadman et al., “The Effect of Decomposition on the Efficacy of Biometrics for Positive Identification,” Journal of Forensic Sciences, (2017).

[9] D. Meuwly, “Forensic individualisation from biometric data,” Science & Justice, 46(4), 205-213 (2006).

[10] D. Meuwly, and R. Veldhuis, "Forensic biometrics: From two communities to one discipline." 1-12 (2012).

[11] “Fingerprints - Crime Museum,” (2017).

[12] S. K. K. M, S. Rajeev, K. Panetta et al., "Fingerprint Authentication Using Geometric Features.", Proc. of IEEE HST (in press), (2017).

[13] S. S. Agaian, M. M. A. Mulawka, R. Rajendran et al., "A comparative study of image feature detection and matching algorithms for touchless fingerprint systems." 2016, 1-9 (2016).

[14] S. Rajeev, S. Kamath K.M, K. Panetta et al., "3-D Palmprint Modeling for Biometric Verification." Proc. of IEEE HST (in press), (2017).

[15] R. Rajendran, [Shafer's textbook of oral pathology] Elsevier India, (2009).

[16] N. Dwivedi, A. Agarwal, B. Kashyap et al., “Latent lip print development and its role in suspect identification,” Journal of forensic dental sciences, 5(1), 22 (2013).

[17] S. Rajeev, S. K. KM, and S. S. Agaian, "Method for modeling post-mortem biometric 3D fingerprints." 98690S-98690S-10 (2016).

[18] W. Chapman, A. Hicklin, G. Kiebuzinski et al., “Latent Interoperability Transmission Specification,” NIST Special Publication, 1152, (2013).

[19] Y. Chen, G. Parziale, E. Diaz-Santana et al., "3D touchless fingerprints: compatibility with legacy rolled images." 1-6 (2006).

[20] A. B. J. T. David Chek Ling Ngo, Jiankun Hu, “Biometric Security”, 497/A5 (2015).

[21] D. Maltoni, D. Maio, A. K. Jain et al., [Handbook of fingerprint recognition] Springer Science & Business Media, (2009).

[22] G. Abramovich, K. Harding, S. Manickam et al., "Mobile, contactless, single-shot, fingerprint capture system." 766708-766708-12 (2010).

[23] Y. Wang, L. G. Hassebrook, and D. L. Lau, “Data acquisition and processing of 3-D fingerprints,” Information Forensics and Security, IEEE Transactions on, 5(4), 750-760 (2010).

[24] Q. Zhao, A. Jain, and G. Abramovich, "3D to 2D fingerprints: Unrolling and distortion correction." 1-8 (2011).

[25] S. Shafaei, T. Inanc, and L. G. Hassebrook, "A new approach to unwrap a 3-d fingerprint to a 2-d rolled equivalent fingerprint." 1-5 (2009).

[26] S. P. Rao, R. Rajendran, S. S. Agaian et al., "Alpha trimmed correlation for touchless finger image mosaicing." 98690U-98690U-12 (2016).

[27] "greasy texture on boat, free photos, #1168708 ", http://www.freeimages.com/photo/greasy-texture-on-boat-1168708, (2017).

[28] M. Cimpoi, S. Maji, I. Kokkinos et al., "Describing textures in the wild." 3606-3613 (2014).

[29] D. Maio, D. Maltoni, R. Cappelli et al., [FVC2004: Third fingerprint verification competition] Springer, (2004).

[30] "Biometric and Forensic Research Database Catalog", https://tsapps.nist.gov/BDbC/Search?page=10, (2017).

[31] S. Agaian, P. Rad, R. Rajendran et al., "A Novel Technique to Enhance Low Resolution CT and Magnetic Resonance Images in Cloud." 73-78, (2016)

[32] K. Panetta, C. Gao, and S. Agaian, “No reference color image contrast and quality measures,” IEEE transactions on Consumer Electronics, 59(3), 643-651 (2013).