The Study of Three-Dimensional Fingerprint Recognition in Cultural Heritage: Trends and Challenges

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Fingerprints play a central role in any field where person identification is required. In forensics and biometrics, three-dimensional fingerprint-based imaging technologies, and corresponding recognition methods, have been vastly investigated. In cultural heritage, preliminary studies provide evidence that the three-dimensional impressions left on objects from the past (ancient fingerprints) are of paramount relevance to understand the socio-cultural systems of former societies, to possibly identify a single producer of multiple potteries, and to authenticate the artist of a sculpture. These findings suggest that the study of ancient fingerprints can be further investigated and open new avenues of research. However, the potential for capturing and analyzing ancient fingerprints is still largely unexplored in the context of cultural heritage research. In fact, most of the existing studies have focused on plane fingerprint representations and commercial software for image processing. Our aim is to outline the opportunities and challenges of digital fingerprint recognition in answering a range of questions in cultural heritage research. Therefore, we summarize the fingerprint-based imaging technologies, reconstruction methods, and analyses used in biometrics that could be beneficial to the study of ancient fingerprints in cultural heritage. In addition, we analyze the works conducted on ancient fingerprints from potteries and ceramic/fired clay sculptures. We conclude with a discussion on the open challenges and future works that could initiate novel strategies for ancient fingerprint acquisition, digitization, and processing within the cultural heritage community.

CCS Concepts: • **Applied computing → Fine arts;**

Additional Key Words and Phrases: Ancient fingerprints, pottery, fired clay sculptures, heritage biometrics

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1 INTRODUCTION

For more than a century, the development of fingerprint-based technology for person identification has been applied in forensics, governmental border control, building security access, and, most recently, in smartphone locking systems, e-commerce, and e-governance applications [36, 56, 68]. The identification of persons via fingerprints is more successful than other biometrics because of the fundamental premises that a fingerprint is persistent/permanent (i.e., a person's physical characteristic/trait that does not change over time) and unique (i.e., the patterns from distinct fingers are different). In forensic science and paleodermatoglyphics (i.e., the study of fingerprints that survive for centuries on the surface of artifacts), research on the relationships between ridge breadth and age [13, 34], and between ridge density and biological sex in diverse ethnic groups [23, 35, 59], have led to the discovery of robust statistical patterns distinguishing adults from children, and males from females. Moreover, evidence shows that similar fingerprint patterns appear in female twins [54], and that the genetic variant influences such patterns [25].

Interestingly, the inference of demographic data (biological sex, age) from fingerprint patterns is investigated as to provide more nuanced understandings about the role of juveniles/adults and men/women in the making process of such artifacts in the past societies [16, 17, 32, 34]. We refer to "ancient fingerprints" as the **three-dimensional (3-D)** impressions left on items by past producers; ancient fingerprints are molds in reverse of the actual prints. A variety of media contain ancient fingerprints [33], yet these are displayed predominantly on ceramic clay, and this is especially due to the clay's plasticity for imprinting, and to the necessity to be molded by bare hands. Examples of artifacts displaying ancient fingerprints (small figurines, utilitarian pots, roof/floor tiles, bricks, vessels) are found during field excavations. Importantly, ancient fingerprints come in different conditions with respect to their original status, as certain treatments may have deteriorated the surface, such as wiping, burnishing, smoothing or polishing. As such, ancient fingerprints displayed on potteries and ceramic/fired clay sculptures collected in museums always appear partial or fragmented. We highlight that we refer to the archaeological artifacts and sculptures as cultural heritage items, namely those objects with exceptional universal value from the point of view of history, art, or science [82].

With this survey, we outline the key similarities and differences between fingerprint-based biometrics as it is used for day-to-day person identification, the opportunities of digital fingerprint recognition in answering a range of questions in cultural heritage research, and the specific problems and challenges that arise when analyzing fingerprints in cultural heritage.

The organization of the manuscript is depicted in Figure 1. First, an overview of the imaging modalities used in the biometrics systems to acquire **two-dimensional (2-D)** and 3-D fingerprints is provided. Next, we explore the literature on the fingerprints features and how these are matched for person recognition, followed by a section on different machine learning methods used in distinct stages of fingerprint analysis. Analogous to the summary on scanning devices adopted in biometrics, an overview of the imaging modalities used in cultural heritage studies is presented together with the research works grounded on fingerprints. To simulate a case study on fingerprint images lifted from fired clay sculptures, we provide a proxy scheme with the basic steps of 2-D fingerprint recognition evaluated on a subset of publicly available images. In conclusion, the challenges and open questions on fingerprint-based research within the cultural heritage domain are discussed.

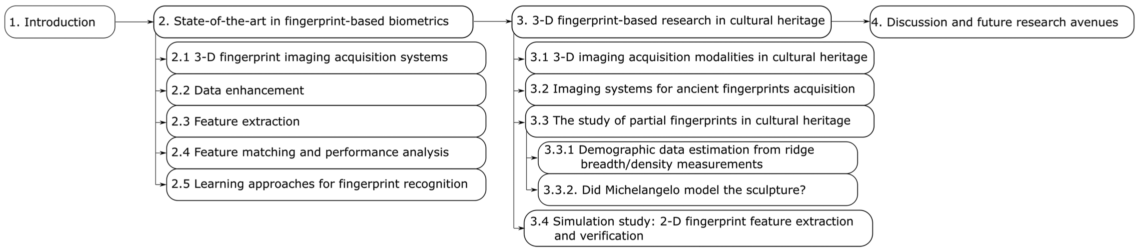

Fig. 1. Organizational chart of the article.

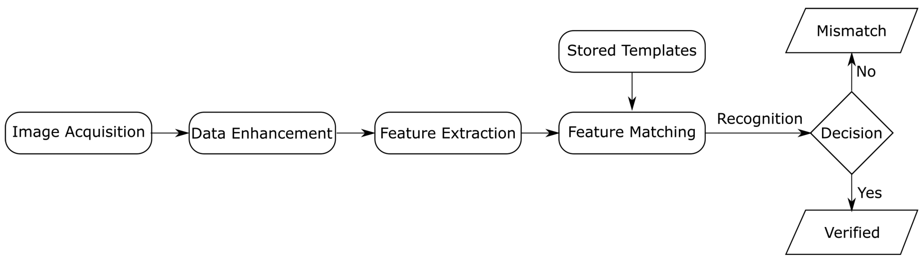

Fig. 2. The schematic outline of Section 2 follows the steps of a standard workflow in fingerprint biometrics. From left to right: The acquisition module reads the input fingerprint and delivers an image that is further enhanced. A postprocessing block is used to determine useful characteristics to be matched against stored characteristics and determine a fitting match. Depending on the matching score, the decision-making unit determines whether the entry user was genuine/imposter.

2 STATE-OF-THE-ART IN FINGERPRINT-BASED BIOMETRICS

Following Figure 2, we examine the main 2-D/3-D fingerprint acquisition modalities, the enhancement strategies for noise removal from raw data, the 2-D/3-D types of features, and how these are matched for person recognition.

2.1 3-D Fingerprint Imaging Acquisition Systems

For decades, the fingerprint-based biometrics community has developed 2-D touch-based devices, which remain the most used technology for authentication worldwide. In general, the user is required to press his/her own fingerprint on a flat surface that represents the front-end interface of a sensor. Unfortunately, the acquired image is often degraded (smearing, slippages, elastic skin deformation, sweat, sensor/finger dirt). To decrease the impact of noise on the image quality and, correspondingly, to improve the recognition accuracy and the identification rate of spoof attacks (e.g., artificial fingerprints, fingerprint tampering), touchless 2-D scanners have been developed. In these systems, the illumination sources could be placed either on the same side as the imaging camera or behind/toward the fingernail side of the finger; in the former, the fingerprint image is generated by the illumination reflected on the finger ridges, whereas in the latter, the resulting image captures the illumination that penetrated the fingerprint. However, contactless 2-D fingerprint systems suffer from low contrast between ridges and valleys, and require further enhancement steps prior to any further feature extraction. To reduce the shortcomings of 2-D touchless devices, 3-D touchless technologies have been implemented (Figure 3).

The structured light 3-D scanner (SLS) utilizes the distortion of projected light patterns onto the fingerprint to obtain its 3-D surface profile using the principle of triangulation (Figure 3(a), Table 1) [47, 87]. This principle implies that the location of the contact point of the beam to the 3-D fingerprint, the camera, and the projector form a triangle that is used to compute the depth information. Such device has attracted growing interest from

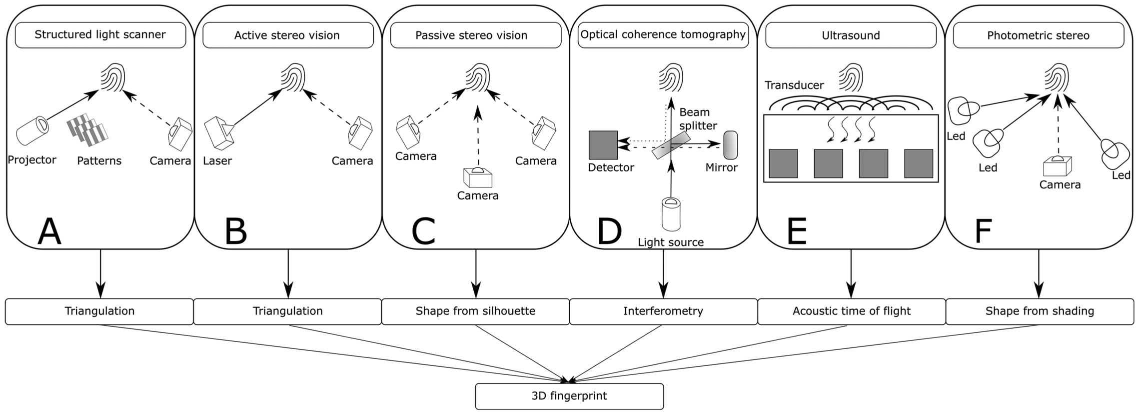

Fig. 3. Schematic overview of the most commonly used 3-D fingerprints touchless imaging devices in biometrics and the corresponding imaging principle for 3-D surface/volume recovery. (a) The projector sends light patterns to the fingerprint; given the location of each stripe and of the corresponding distorted projection, the full 3-D model is recovered. (b) The 3-D fingerprint is hit by a laser beam and the signal response is captured by the camera; the exact position of the camera and the source allows to recover the exact 3-D location of each point. (c) More than two cameras are positioned at different angles around the fingerprint and shoot simultaneously; the reconstruction is possible given the exact spatial location of the cameras and their correspondingly matching spatial points. (d) The light beam emitted by the source penetrates the finger skin; the location of the mirror is in equal path from the beam splitter as the location of the finger. The beam splitter separates the input light beam into a component that is reflected to the mirror and another that hits the finger. The light reflected from the mirror (dashed line) and the finger (dotted line) is collected by the detector. (e) An ultrasonic pulse is transmitted by a transducer against the finger that is placed over the scanner; the pulse can be absorbed or reflected to the scanner, depending on the fingerprint structure. (f) Multiple 2-D fingerprint images are acquired from a fixed viewpoint/camera under different illumination sources (LEDs).

both researchers and practitioners, especially for its use in the documentation and storage of plastic prints as opposed to traditional photographs [94], and for the acquisition of fingerprints from fingers of living/deceased individuals [62]. A 3-D SLS captures the full field of view at once, which significantly increases the scanning speed and considerably reduces noise emerging from motion. However, these scanners display poor performances in handling of translucent materials and misalignment in the data modeled by each pattern, and are characterized by lower resolution than other laser-based triangulation methods. Stereo vision systems also compute the depth information using the triangulation principle [36]. Active stereo vision systems use a digital camera that records the response from a known laser signal [31], after its projection to the 3-D finger surface (Figure 3(b)); however, these strategies are vulnerable to high-frequency noise and finger motion during acquisition. In passive stereo vision systems, the laser source is substituted with a second camera and a cylindrical model for the presented finger is generated using silhouettes from each acquired image (Figure 3(c)) [40, 49, 63]. Shape from silhouette approaches lack details on the fingerprint ridge information that is essentially derived from the surface reflection variation (i.e., albedo) information, thus being affected by skin pigmentation, surface reflectance, and finger shape. Another challenging step in passive stereo vision is determining accurately the location of correspondence points in two images taken from different 3-D views. Recently, the use of **optical coherence tomography (OCT)** has expanded the research frontiers on 3-D touchless fingerprint recognition [10, 48, 85]. OCT acquires the information beneath the fingertip skin up to 2 to 3 mm and reconstructs the fingerprint using the principle of interferometry (Figure 3(d)), where light reflected from the finger skin is combined with light reflected from a reference mirror in an attached detector; the depth information is retrieved using the spectral modulations in the interference patterns between the light reflected by the reference mirror and the finger surface layers. OCT 3-D

Table 1. Summary of 3-D Fingerprint Image Acquisition Systems

Method	Source Data	Cost	Accuracy	Reference	Year	Resolution	Capture Time
Structured light imaging	Range image	Moderate	High	Zhang et al. [94]	2020	SLI_1: < 12 μm; SLI_2: 0.1 mm	SLI_1: N.A.; SLI_2: 7.5 fps
				Panetta et al. [62]	2019	~1,344 ppi	0.7 s
				Liu et al. [47]	2017	380 dpi	N.A.
				Wang et al. [87]	2010	~1,344 ppi	<1 s
Active stereo camera	Range image	High	High	Kanhangad et al. [31]	2011	HR: 640 × 480 pixels; LR: 320 × 240 pixels	HR: 2.5 s; LR: 0.3 s
Passive stereo camera	Range image	Low	Low	Labati et al. [40]	2015	Camera image: 1,280 × 960 pixels	529 μs
				Liu & Zhang [49]	2014	~400 dpi	100 ms
				Parziale et al. [63]	2006	500–700 dpi	120 ms
Optical coherence tomography	Backscattered light amplitude	High	High	Wang et al. [85]	2020	Z-direction of A-scan: 7 μm	N.A.
				Liu et al. [48]	2020	Axial: 8 μm; Lateral: 12 μm	N.A.
				Chugh & Jain [10]	2019	Axial (Air/Water): 5.5 μm/4.2 μm	<1 s
Ultrasound	Acoustic impedance	Low	Moderate	Jiang et al. [28]	2017	Axial: 150 μm; Lateral: 75 μm	N.A.
				Lu et al. [53]	2015	Axial: 68 μm; Lateral: 60 μm	N.A.
Photometric stereo	Surface normal orientation	Low	High	Lin & Kumar [45]	2017	1,400 × 900 pixels	Two shots: ~250 ms; Three shots: ~800 ms
				Kumar & Kwong [37]	2013	2,592 × 1,944 pixels	10 fps
				Xie et al. [89]	2013	659 × 493 pixels	<0.1 s

Method: 3-D fingerprint acquisition technology; Source Data: 3-D fingerprint image representation; Cost: device cost estimate; Accuracy: reconstruction accuracy estimate; Reference: reference to relevant studies in biometrics; Year: year of publication; Resolution: resolution of the camera (in pixels, dpi, ppi) or the step of the grid (in millimeters) that the algorithm uses to reconstruct a polygonal model; Capture Time: scanning time (in fps, s, ms); N.A.: information not reported in the paper/manual; HR: high resolution; LR: low resolution; SLI_n: n-th Structured Light Imaging device.

fingerprint-based imaging is invariant to skin damage and is less sensitive to spoof attacks. Another example of 3-D touchless strategy is ultrasonic imaging, where the 3-D fingerprint is reconstructed based on the acoustic time of flight (Figure 3(e)) [28, 53], which measures the time that the acoustic pulse travels from the transmitter to the fingerprint, and backward to the receiver. Even though ultrasound-based sensing technology delivers high-resolution images, its voluminous hardware makes it less attractive compared to other 3-D touchless devices; moreover, despite the increase in ultrasonic 3-D imaging techniques, touchless 3-D fingerprint recognition based on ultrasonic images is yet to be attempted in the literature. Among the 3-D fingerprint touchless methods, photometric stereo is the most widely used approach because it combines affordable costs with high-frequency fingerprint ridge details [37, 45, 89]. This system consists of multiple 2-D fingerprint images acquired from a fixed viewpoint/camera under different illuminations (Figure 3(f)). Given the locations of fixed illuminations, the fingerprint is reconstructed by calculating the 3-D surface orientations. Unfortunately, involuntary finger motion may occur during the acquisition and deteriorate the reconstruction accuracy.

2.2 Data Enhancement

In general, the data enhancement stage is required prior to any 2-D/3-D feature extraction method. The enhancement strategy recovers the ridge pattern from unwanted noise occurring during scanning/reconstruction by connecting interrupted ridges, separating incorrectly joined ridges, and removing overlapping patterns. In the 2-D fingerprint domain, the enhancement methods could use filters [21, 26, 86], include the prior knowledge of the fingerprint structure [29], apply distinct frequency bands at different image scales [19, 42], and implement methods based on tensors and their decomposition [41]. In the context of 3-D fingerprint touchless devices, such as photometric stereo and SLS, a median filter is used to suppress speckle-like noise on the input point cloud

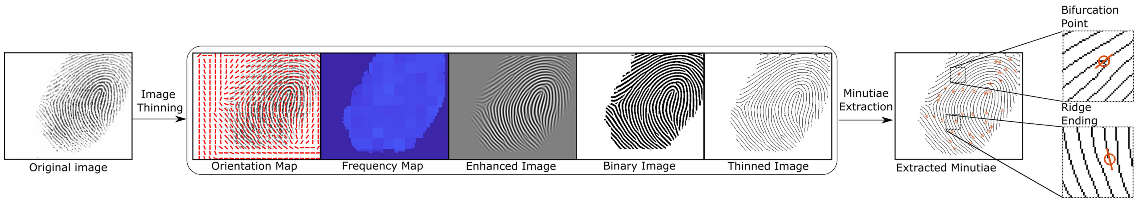

Fig. 4. Schematic overview of a filter-based thinning process, followed by minutiae extraction and matching. The orientation field/map (red oriented lines) indicates the block-wise average ridge orientation. In a frequency map, the brighter the color of a block, the denser the ridges in that area. The minutiae can be, for example, the bifurcation points and split ends (colored markers), both represented with their corresponding orientations (colored lines). The image is taken from the FVC2002 1A database.

(i.e., each point is expressed with its x, y, z–location in the 3-D space), which is then subjected to further 3-D smoothing [37].

2.3 Feature Extraction

A feature/pattern is a measurable property/characteristic that uniquely determines a fingerprint and can be used to differentiate distinct impressions. In the authentication settings, a set of features from a fingerprint (probe/query) of a person with unknown identity are compared against the features from fingerprints (templates) of known individuals stored in a database/gallery; the result of each matching is a probability score that expresses how well the probe matches the templates. In traditional fingerprint recognition systems, the most commonly used features from the 2-D touch-based or touchless generated image (with resolution of at least 500 dpi) correspond to the global ridge patterns (ridge orientation fields) and local ridge singularities known as minutiae points [36] (Figure 4). Fingerprint images can be considered as an oriented texture pattern. As such, the ridge orientation field indicates the optimal dominant ridge direction in each squared window/block of the input image, and it is calculated using the horizontal and vertical gradients within each window/block. Since the early inception of an enhancement process for touch-based fingerprint images [26], the orientation field serves to select the parameters of adaptive filters in subsequent stages. Local ridge frequency is another intrinsic property of a fingerprint image: in a local neighborhood where no minutiae appear, the gray levels along ridges/valleys are modeled as a sinusoidal-shaped wave along a direction normal to the local ridge orientation. As such, given the mean orientation within the block, the spatial frequency of the ridges is determined by dividing the distance between the first and last peaks by the number of peaks found in the block. If no peaks are detected, or the wavelength is outside the allowed bounds, the frequency image is set to zero. Finally, using the orientation and frequency maps, the filters corresponding to these distinct frequencies and orientations are computed. The resulting filtered image appears enhanced—that is, the ridge/valleys alternate and flow in a locally constant direction (Figure 4). The most traditional approach for minutiae extraction is based on the thinned ridge patterns, namely those patterns where each ridge is converted to one pixel width after the enhancement stage. The enhanced image is transformed to binary image that is usually further thinned; in the thinned image, ridge structures are reduced to one pixel width (skeleton), to aid minutiae detection. As such, the resulting thinned binary image has each pixel analyzed to find the minutiae location. A minutia is commonly described with its x, y-coordinate, the angular direction of the main ridge, and type (e.g., bifurcation, ending). Minutiae detection is achieved by having the eight-neighborhood circularly traversed in an anti-clockwise manner to produce the Rutovitz crossing number, which allows the identification of ridge endings/bifurcations.

Since the majority of fingerprint recognition systems have been developed in 2-D, substantial research has been dedicated to the detection of 2-D features from the unwrapped/unrolled representations of 3-D fingerprints [39].

Despite the impressive performance of biometric systems using 2-D global/local patterns, the rise of 3-D and high-resolution imaging have recently attracted increasing attention to generate a novel set of features [50, 51, 90], such as principal curvatures, the 3-D minutiae, and tetrahedron [36, 37, 45]. A recent work has focused on 2.5-D ridge pattern representation and image processing techniques to perform a full 3-D fingerprint recognition [20].

2.4 Feature Matching and Performance Analysis

In general, the main focus of 2-D/3-D minutiae-based matching is to perform a one-to-one mapping/pairing of minutiae points from a test minutiae set to a template minutiae set [36]. Since minutiae-based matching has limited performance in case of missing minutiae and non-linear fingerprint deformations, alternative approaches have been proposed, such as the topology-based and correlation-based matching in the 2-D domain, and tetrahedron matching in the 3-D space. In standard biometric practice, the matching is evaluated by two distinct operative modes: the identification and verification setups. In the biometric identification setup, a one-to-many comparison of probe fingerprint with multiple fingerprints stored in a gallery is performed. The identity is established by looking at the best-matching candidates after sorting the gallery from highest to lowest matching scores. In the biometric verification setup, a one-to-one comparison with a single fingerprint candidate is performed. The performance is evaluated using receiving operating characteristic analyses. For a range of thresholds on the matching score, the true positive fraction is plotted against the false positive fraction. Performance values that are generally reported are the **area under the curve (AUC)** and the **equal error rate (EER)**, which is the point where the fractions of true and false positive are equal. Higher AUC and lower EER values indicate better performance.

2.5 Learning Approaches for Fingerprint Recognition

The advances in 2-D/3-D fingerprint acquisition technologies and the successful usage of deep **convolutional neural networks (CNNs)** for a range of computer vision problems [77, 81, 93] have attracted researchers to use neural networks for fingerprint recognition tasks. The problem of minutiae extraction in 2-D plain fingerprints (i.e., finger impressions against a flat surface) is challenged by the fingerprint quality, unwanted fingerprint motion, and scanner conditions. The traditional enhance-thinning-extract trilogy is outperformed in accuracy and robustness by automatic minutiae detection algorithms established on deep neural networks [12, 27, 60]. Similarly, a deep learning–based pipeline applied on rolled and slap fingerprints (i.e., nail-to-nail impressions and multiple flat fingerprints captured at the same time, respectively) has shown promising results [80], outperforming the state-of-the-art minutiae extraction algorithms. Several efforts have also been dedicated to automatic minutiae detection from latent images (i.e., impressions lifted from the surfaces of objects) using CNN-based algorithms [60, 79]. Moreover, CNNs have also been implemented to enhance the overall image quality, without the need of estimating actual orientation maps to perform enhancement [43], and to implement an alternative strategy for latent/partial fingerprint segmentation [84]. Despite the advances on deep learning methods on contact-based images, research on deep learning methods applied on contactless 2-D images has received little attention. In these settings, the finger excessive rotations and incorrect alignments are hard to control and can significantly degrade the matching accuracy of the biometric system. Efforts have been addressed toward pose compensation using neural networks [78].

Several publications have investigated 3-D shape recognition using approaches based on CNNs [22, 67, 75, 88]. Since most of the fingerprints found on ceramic/fired clay sculptures and potteries are incomplete, the study of partial 3-D fingerprints in biometrics is particularly interesting for the cultural heritage domain. Essentially, partial fingerprints in biometrics occur from the unintentional rotation of fingers in the 3-D space. Although existing methods have improved the recognition of 2-D partial fingerprints, partial 3-D fingerprint recognition has attracted less attention. We cite the work of Lin and Kumar [46] as a preliminary attempt for partial 3-D fingerprint recognition using deep learning.

Interestingly, different algorithms have been implemented for fingerprint 2-D image generation [76, 91]. As a matter of fact, research on partial 3-D fingerprint recovery is currently missing.

3 3-D FINGERPRINT-BASED RESEARCH IN CULTURAL HERITAGE

Despite the successes of 3-D fingerprint-based technologies, and the evidence that fingerprints can contribute to the identification of makers, cultural heritage research on 3-D fingerprints has lagged behind. These delays have various origins.

Ancient fingerprints are always partial and have long been considered by archaeologists as physiological traits carrying poor information content, and thus, even though listed in the records, these have been neglected. In archaeology, fingerprint-based research contrasts with approaches based on ethnographic analogy and cross-cultural comparisons [32]. In this sense, the latest studies based on 2-D fingerprint acquisitions represent already a major contribution to the field [16, 17, 32].

Ancient fingerprints are delicate and transient, posing challenges for sample collection, transportation, and storage. The use of 2-D cameras is a common choice for archaeologists when other collection methods are not suitable. 2-D cameras are easy to transport and use in excavations sites, the acquired images are quickly enhanced on commercially available software, and they are less expensive devices than complex ones. However, the irregular shape of the object can distort the perspective of traditional photography, the object aging reduces the fingerprint visibility, and there is actual chance that fingerprints are left on hard-to-reach patches even by an experienced operator. Moreover, the transient nature of ancient fingerprints poses a risk of destruction during measurement procedures.

The value and fragility of artworks stored in museums require trained experts who are proficient in imaging computational methods. Often, museum research laboratories rely on a third party that is equipped with the necessary setup and knowledge. An additional issue refers to the lack of research budgets, which hampers the progress for this kind of fundamental research.

In this section, we provide an overview of the distinct imaging techniques for object acquisition in cultural heritage, together with a list of imaging strategies tailored to ancient fingerprints from potteries and ceramic/fired clay sculptures. This is then followed by a report on different types of studies based on ancient fingerprint images and a simulation study on 2-D fingerprint recognition.

3.1 3-D Imaging Acquisition Modalities in Cultural Heritage

In cultural heritage, the fragility and value of artworks and archaeological items impose the use of non-contact and non-destructive acquisition techniques. Most of the acquisition setups in museum workshops and studios are used to investigate the conservation condition and the monitoring of the restoration treatments, as well as to allow the general public to have access to the museum artworks, either through a digital archive or physical replica printed from the scanned item [18, 24, 57, 64]. Some of the most used technologies include laser-based systems for artworks' structural diagnostics [5, 8, 15, 70], structured light scanning for documentation and data interpretation [6, 71], photogrammetry for object decay assessment, digitization, texture visualization, data acquisition ranging from small items to historic buildings [1, 2, 92], and 3-D **computed tomography (CT)** for full volume inspection [7, 58]. For example, 3-D CT scanning has helped restorers reconstruct the fragments of the damaged sculpture "Adam" at the Metropolitan Museum of Art in New York [83]; the experts used computational imaging as a valuable diagnostic tool to analyze the cracks of the sculpture, as opposed to more traditional methods that would have implied a faster and more invasive restoration approach. In dendroarchaeology, the discipline that investigates the dating of wooden objects, 3-D imaging research has provided a major impact on the study of cultural heritage objects; for instance, 3-D magnetic resonance imaging and CT are used to measure tree rings of musical instruments, historic buildings, artifacts, and art objects [14]. Moreover, progress has been made in the combination of distinct techniques to obtain complementary information. The scanning and the reconstruction of delicate glass items of marine invertebrates made by Rudolf and Leopold Blaschka in the late 19th century is a prime example [18]. Fried et al. [18] combine photogrammetry (high-resolution texture information) and CT scanning (high-resolution structure information) to digitize masterpieces that are considered challenging to scan. Along this line, photogrammetry coupled with virtual, mixed, and augmented reality allows to recreate, examine, and visualize archaeological sites, architectural buildings, sculptures, and ceramic tiles, and silver, marble, and wooden artifacts [3, 9].

3.2 Imaging Systems for Ancient Fingerprints Acquisition

The acquisition of fingerprints by contactless acquisition imaging systems on ceramic/fired clay sculptures or potteries reduces the errors of direct measurements, like with calipers. The key difference between the fingerprint acquisition systems in biometrics as opposed to cultural heritage is that the former is usually tailored on the active participation from the subject, both in the 2-D and the 3-D settings; in contrast, the latter is based on the notion that fingerprints are always left inadvertently, often by a producer from the past in the act of sculpting or pottery making, and that these impressions are typically found on less conspicuous parts of sculptures and often hidden from view in the internal voids. The fingerprint-based research in cultural heritage is currently sparse and uncatalogued. As such, Table 2 provides a comprehensive list of fingerprint-based studies, or works where fingerprints have been detected during an object inspection. In general, contactless multi-camera systems are of preference in cultural heritage to scan large and precious items; however, such systems are complex and challenging to transport in excavation sites, and they are not ideal to acquire small patches such as fingerprints. Sanders [72] uses 2-D images of ancient fingerprints to infer the sex of the maker from vessels found in Tell Leilan in northern Mesopotamia (Syria). Fowler et al. [17] investigate the sex and age from 2-D images of ancient fingerprints found with exceptional preservation quality. Ceramic sherds are scanned at high resolution (600 dpi) on a flatbed scanner, photographed on a flat tabletop using a digital single-lens reflex camera. In addition, they use a high-resolution camera from a commercially available smartphone; photographs from either type of camera produce images from which the measurements of epidermal ridge breadths are more accurate than those from the scans. All images are contrast/exposure adjusted in Photoshop; consequently, the enhanced images are calibrated for measurement in Macnification. The same acquisition settings are adopted by Fowler et al. [16], where a larger dataset of ancient fingerprints is acquired from the same geographical region and historical period. Similarly, Kantner et al. [32] study the sex-based labor division based on ceramic sherds acquired with a stereo microscope and a high-resolution camera. The work of Lichtenberger and Moran [44] investigates the ancient fingerprints detected on Late Roman oil lamps and figurines. The 2-D fingerprint images are used to locate the minutiae across multiple and distinct clay items. Bennison-Chapman and Hager [4] apply Reflectance Transformation Imaging to fingerprints on Neolithic clay "tokens." The subject is shot from a stationary camera position, and light is projected from a different known direction for each photograph. Eventually, a polynomial texture map is generated based on the pattern of light reflection from the surface under study, and based on the color data in each acquired image.

In the context of fingerprints found on sculptures, Lloyd [52] analyzes fingerprints on sculptures that are associated with the sculptor Gian Lorenzo Bernini (Italy, 1698–1680). Each image, representing one fingerprint, is preprocessed before being printed and given to a forensic expert for identification. The work of Labati et al. [38] is an early attempt to scan and reconstruct the 3-D fingerprint on a clay artwork associated with the sculptor Antonio Canova (Italy, 1757–1822). In their setup, the patch displaying the fingerprint is placed in the middle of two cameras shooting at the same time, and the camera geometry is used to establish the reconstruction model. Their proposed approach establishes a metric, view-independent, and less distorted reconstructed models when compared to 2-D photographs. Ancient fingerprints on sculptures are often detected during the documentation

Table 2. 3-D Fingerprint-Related Publications in Cultural Heritage

Reference	Year	Sample	Producer	Period	Device	Image Processing
Rees-Jones [69]	1978	Terracotta relief "Madonna and Child"	School of Verrocchio	c. 1460s	2-D camera	N.A.
Kamp et al. [30]	1999	Sinagua clay vessels	Ancestral Pueblan groups, northern Arizona	N.A.	Digital calipers	N.A.
Lloyd [52]	1999	13 clay sculptures	Gian Lorenzo Bernini (1598–1680)	N.A.	2-D camera	Outlier removal, image sharpness/color adjustment, gray-scale conversion
Králík, Novotný [34]	2003	Three groups (I, II, III) of terracotta samples	(I) 56 children; (II) 20 adult professional ceramists; (III) 30 non-professional ceramists	c. 2003	2-D camera	Contrast enhancement, calibration
Stinson [74]	2004	Ancient ceramic Hohokam figurines	Southwestern Native American and Filipino communities	c. 300 B.C.–A.D. 700 and A.D. 700–900.	2-D camera, microscope	Calibration prior measurements
Labati et al. [38]	2012	Terracotta sketch of "Ninfa dormiente"	Antonio Canova (1757–1822)	N.A.	Two 2-D cameras	3-D model reconstruction with triangulation; surface/texture maps generation
Sanders [72]	2015	101 ceramic vessels	Tell Leilan community, northern Mesopotamia (Syria)	c. 3400–1700 B.C.	2-D camera	Image contrast enhancement, calibration
Lichtenberger & Moran [44]	2018	Oil lamps, clay figurines	Beit Nattif workshop (Israel)	c. 300 A.D.	2-D camera	Contrast adjustment, calibration, 2-D-based manual minutiae detection
Bennison-Chapman & Hager [4]	2018	88 clay objects.	Neolithic village communities	c. 8500–7500 B.C.	Reflectance transformation imaging	Polynomial texture maps
Fowler et al. [17]	2019	18 clay vessels	Tell eṣ-Ṣafi/Gath community (Israel)	c. 2850–2500 B.C.	2-D camera, flatbed scanner, smartphone camera	Contrast/exposure adjustment, calibration
Kantner et al. [32]	2019	985 ceramic sherds	Ancestral Puebloan community in the U.S. Southwest	c. 900–1100 A.D.	2-D camera, stereo microscope	Contrast enhancement, calibration
Coban et al. [11]	2020	One terracotta sculpture from the Rijksmuseum (BK-2016-44-4)	Johan Gregor van der Schardt (1530–1591)	c. 1560–1570	CT scanner	3-D tomographic reconstruction
Fowler et al. [16]	2020	47 clay vessels	Tell eṣ-Ṣafi/Gath community (Israel)	c. 2850–2500 B.C.	2-D camera, flatbed scanner, smartphone camera	Contrast/exposure adjustment, calibration

Authors: authors of the study; Year: year of publication; Producer: the object artisan or the community of artisans (if known); Period: the historical period of the item/s; Device: the acquisition method/s; Image Processing: any data postprocessing method to enhance the image; N.A.: information not reported or not investigated.

and restoration procedure. An example refers to the terracotta sculpture "Madonna and Child" attributed to the School of Verrocchio [69]. More recently, Coban et al. [11] showed how the CT scanner at the FleX-ray Laboratory facility at CWI (Amsterdam) allows the detection of a 3-D fingerprint hidden in a hollow of a terracotta sculpture from the Rijksmuseum and attributed to Johan Gregor van der Schardt (1530–1591). The fingerprint pattern is clearly distinct from an aliasing effect that may arise during the reconstruction process. Interestingly, the hidden position of the fingerprint makes CT highly desirable to uncover the impressions of unknown and hard-to-reach locations, even to the museum restorer/curator.

3.3 The Study of Partial Fingerprints in Cultural Heritage

The study of fingerprints in cultural heritage is essentially focused on two distinct assignments. First, given an estimate of sex/age from ridge breadth/density measurements, experts are able to compose the demographic structure of the making groups and draw wider conclusions on the organization of the society they lived in. Second, researchers investigated partial/degraded fingerprints in an attempt to find a single signature or confirm the identity of who they acknowledged to be the author. Usually, the first case requires a conspicuous amount of data (e.g., almost 1,000 sherds in the work of Kantner et al. [32]), whereas the second is based on one/few objects. In the next paragraphs, we treat the key aspects of ancient fingerprints (partial/degraded) in relationship to their usage.

3.3.1 Demographic Data Estimation from Ridge Breadth/Density Measurements. Several research studies investigate the organizational structure of ancient populations by analyzing the partial fingerprints observed on the surface of potteries [16, 17, 30, 32, 72, 74]. Experimental data have shown that even when prints are partial, and neither the finger nor the portion that they represent can be identified, the high correlation between ridge breadth and age, and similarly the correlation between the ridge density and sex, allows for the estimation of age/sex of the producer sufficient for separating the prints of adults and those of children, and fingerprints of men from those of women. In the literature, the ridge breadth is most commonly defined as the beginning of one ridge to the initiation of the next, across the ridge and valley [30]. Since using a caliper for direct measurements can pose challenges for accurate data acquisition, the mean ridge breadth (i.e., the average ridge-valley pairs in the investigated area) is often used in the regression model to estimate age [16, 17, 30, 34]. To determine sex, the ridge density is calculated as the number of ridges counted in a predefined area and compared to a threshold for sex attribution [4, 16, 17, 32, 72, 74].

3.3.2 Did Michelangelo Model the Sculpture? In cultural heritage, an interesting case scenario is the authentication of a sculpture based on the fingerprints lying on the surface. Artworks made with clay often show the imprints left by the maker's hands during the modeling process. During the technical investigation of ceramic/fired clay sculptures, conservators record every single mark left during the production process. Among these remains, fingerprints are probably the most personal clues left by the maker and are typically found on less conspicuous parts of sculptures, such as the base or reverse side, but can also be hidden from view in the internal voids, as the surface of the object may be smoothed leaving no traces of the maker's hands. Despite the good condition of an artwork, the majority of fingerprint patterns are only partial. This may originate, for example, from scratching the surface against some other material, and/or it may be the only part of the finger used during the modeling of the clay. Here, we use the assignment of a terracotta sculpture attributed to Michelangelo as an example and ask the following questions:

- *Do all of these fingerprints belong to Michelangelo?* To prove a match between two impressions on a sculpture, the two impressions have to exhibit matching minutiae—that is, their locations and orientation angles have to be equal within certain bounds. It is important to highlight that in forensics, experts discuss results in probability terms and a fingerprint evidence is never treated as sufficient proof to convict. In the best case scenario, these fragmented fingerprints may contain enough details to be matched against each other. The easiest case is when the sculpture exhibits only one pair of fingerprints: if these are matching, and the name of Michelangelo is known from the records, then we can attribute the impressions with a reasonable degree of certainty to him. In case of multiple matching fingerprints, the challenge is to assign a single signature. For example, if two distinct impressions of an index finger match, and two impressions from the middle finger match as well, it remains to declare if one pair belongs to the right hand of Michelangelo, or if one belongs to the right hand and the other one to the left hand, or if they come from distinct makers. Empirical approaches to determine the handedness of the author exists [69]. In particular, the matching is challenging due to fragmentary and overlapping fingerprints, and their degradation level. Nevertheless, evidence shows that fingerprints impressions can be preserved extraordinarily well and a peculiar ridge pattern is visible at naked eye [44], thus leading the authors to identify a single producer.

- *Who was the producer?* It is rather hard to provide the identity of the sculptor given that there is no database of fingerprints from known artists, unless this information is recorded; even if a common fingerprint across sculptures is detected, the name of the author may not be declared. If multiple sculptures attributed to Michelangelo display matching fingerprints, and the dates of the commissioned works match, then we could have an argument in favor of Michelangelo.
- *What does a matched pair of fingerprints suggest about the role of Michelangelo in the work's production?* Interestingly, depending on the location and amount of the matching fingerprints, we can draw some conclusions on the role of the artist. For example, Lloyd [52] observes two matching fingerprints at different locations in two separate *bozzetti* from Bernini, thus suggesting that the artist was involved in the realization of the whole shape.
- *How can we claim a non-match?* Two impressions are not matching if the amount of similarity between the two sets of minutiae is insufficient to make a corresponding match. Unfortunately, a non-match could also be declared erroneously when two impressions are from the same finger but represent two distinct areas of it. This process is further complicated by the condition of the impression.

The authentication of a ceramic/fired clay sculpture is an assignment that has been little addressed in the literature. Novel 3-D imaging technologies and computational imaging methods could introduce unprecedented analysis on ancient fingerprints, and stimulate the scientific discussion and interdisciplinary collaborations in the field.

3.4 Simulation Study: 2-D Fingerprint Feature Extraction and Verification

In this section, we describe a simulation study that was carried out to assess how well fingerprints can be detected in various scenarios related to cultural heritage research. Specifically, we focus on partial fingerprints, where the size of the fingerprint regions that can be extracted is varied. The goal is to assess—in a controlled setting—the potential for extracting useful information from partial fingerprints with different degradation characteristics. Here, the enhancement strategy is based on the the enhance-thinning-extract trilogy, followed by the matching of minutiae points and matching evaluation on the FVC 2002 1A database [55].

Let us assume that we have a certain amount of fired clay sculptures with fingerprints at our disposal. Suppose we are allowed to use forensic tools to "lift" each fingerprint and capture each impression with a 2-D camera with 500-dpi resolution. The database consists of 100 different fingers with eight distinct impressions for each, for a total of 800 impressions. Each fingerprint is complete, and the ridge/valley patterns are not clear enough to extract features of interest directly from the acquired images. The minutiae x, y-location, type, and orientation are considered to be the most distinctive characteristics for conventional 2-D fingerprint recognition. Here, the method of minutiae extraction requires the gray-scale image to be enhanced and then converted to a skeletonized/thinned binary image. We use the filter-based enhancement scheme described in Figure 4. Briefly, we first generate the orientation map that indicates the dominant ridge direction in each squared window/block of size 16×16 pixels of the input image. Next, we separate the background from foreground image according to block-wise standard deviation. Given the mean orientation within a block in the foreground image, the spatial frequency map is determined by counting the number of peaks in each block. Finally, the filters corresponding to the distinct frequencies and orientations are computed, and this results in an enhanced image containing clear ridge/valleys patterns.

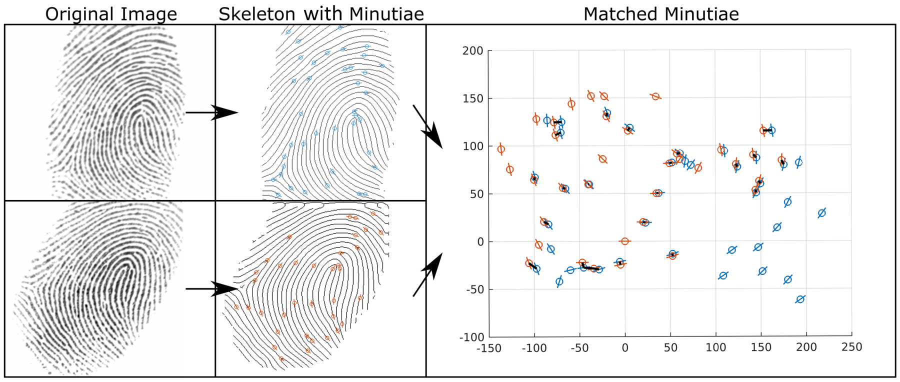

Fig. 5. Minutiae matching from two thinned impressions. Each 2-D image is thinned after a filter-based enhancement scheme. Given the thinned image, the bifurcation points and split ends (colored boxes), with corresponding orientations (colored lines), are extracted by using the information of neighboring pixels in the thinned image. The two sets of minutiae are then rigidly aligned until the highest matching score (i.e., the ratio between the total count of paired minutiae and the product of the minutiae counts per image) is found. The paired minutiae are connected with a continuous black line. Each image (500 dpi) belongs to the FVC2002 1A dataset.

We then transform the enhanced image to a binary image, which we process further using a morphological thinning operation, where ridge structures are reduced to one pixel width, referred to also as the skeleton. We highlight this is only one possible approach for data enhancement from a gray-scale image; for instance, some prefer using an enhanced image without thinning, as the minutiae found on a thinned image may be challenging to overlap to the original image. Minutiae detection is achieved on the thinned image by counting the neighboring pixels of a central one within each block. Once the minutiae are extracted from each image, they are then matched against each other by means of registration (Figure 5). The registration concerns the alignment and overlay of the template and test fingerprints so that corresponding regions of the fingerprints have minimal geometric distance to each other. Registration can be achieved by applying an affine transformation, which takes into account minutiae locations, angles, and type. Following the registration process, we can produce geometric constraints for the discovery of minutiae matching pairs, including geometric distance, and minutiae angle difference. Once true minutiae pairs are produced, a metric of similarity can then be calculated, taking into account how similar each pair is in terms of location, angle, and type. Once the minutiae are extracted from each image of the 800 data of the pool, a recognition pipeline is implemented. Since the verification setup is preferred to compare results across multiple studies [65], we evaluate the recognition performance by a receiving operating characteristic analysis (Table 3, see Figure 7). The verification evaluation consists in the following steps: each sample in the database is matched against the remaining samples of the same finger to compute the genuine rate; the total number of genuine tests is $((8 \times 7)/2) \times 100 = 2{,}800$. The first sample of each finger in the subset is matched against the first sample of the remaining fingers in the database to compute the imposter rate; the total number of imposter tests is $((100{*}99)/2) = 4{,}950$. Using the intact images, we are able to correctly authenticate 2,632 out of 2,800 genuine matches and 4,653 out of 4,950 true imposters.

It is important to highlight that the quality of the input data heavily influences the recognition performance, leading to an increase in false-positive rates. For example, let us assume that the same producers worked on other six datasets of fired clay sculptures that, due to distinct refinement processes, can be divided into two big groups (Figure 6), each dataset containing again 100 different fingers with eight distinct impressions. One group is characterized by images cropped in height of increasing width, and the other one contains images where random blocks are removed. The former has fingerprint images of "predefined deletions" and contains

Fig. 6. Left: Original image from the FVC 2002 1A dataset. Top row, left to right: Image deletions corresponding to 13%, 26%, and 40% of the whole image. Bottom row, left to right: Image deletions corresponding to 10%, 30%, and 50% of the whole image.

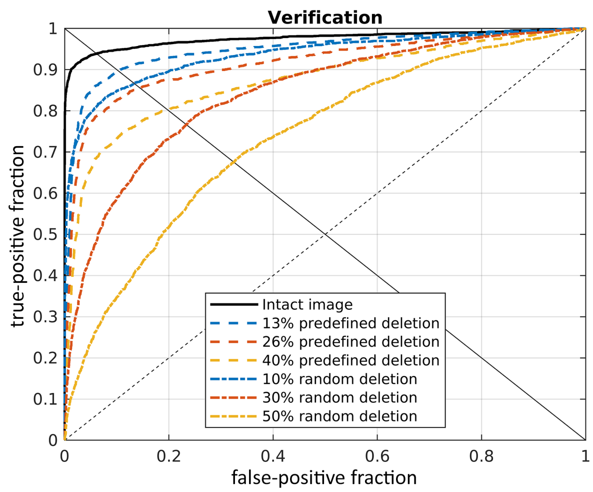

Fig. 7. Verification results for the database FVC2002 1A under different levels of degradation. An image undergoes a predefined deletion when horizontal slabs of increasing widths are removed from the top to the bottom of the image; instead, random deletions refer to the cancellation of squared areas randomly located throughout the image. The deletion is expressed as the total amount of pixels deleted from the image. Using the intact image, 2,632 out of 2,800 genuine matches (true-positives) and 4,653 out of 4,950 imposters (true-negatives) were correctly identified. Different runs for the intact image and the percentages of horizontal and random deletions are plotted as solid, dotted, and dash-dotted lines, respectively.

three datasets where the fingerprint area has been removed by 13%, 36%, and 40%; the second group of "random deletions" contains the remaining three groups where blocks of 16×16 pixels have been deleted, thus removing 10%, 30%, and 50% of the fingerprint area. For each dataset, the same pipeline as for the intact images was followed (i.e., data enhancement, minutiae extraction, and matching). From Figure 7 and Table 3, we observe that the verification power decreases as more sections of the fingerprint image are gradually removed.

4 DISCUSSION AND FUTURE RESEARCH AVENUES

Fingerprints play a central role in any sector where person authentication is required; in fingerprint-based biometrics, enormous advances have been accomplished from imaging acquisition technologies to feature extraction

Table 3. Verification Values for the Database FVC2002 1A Under Different Levels of Degradation

Image Characterization	EER	AUC
Intact image	6.18	97.55
13% predefined deletion	10.18	94.79
26% predefined deletion	14.43	91.50
40% predefined deletion	19.64	87.18
10% random deletion	13.32	93.50
30% random deletion	23.36	84.07
50% random deletion	32.47	73.27

Note: All values are given in percentage. Random performance is given as EER = 0.5, AUC = 0.5. EER: Verification equal error rate; AUC: verification area under the curve.

methods. In cultural heritage, the interest to identify the makers of artifacts based on left fingerprints is tangible [16, 17, 32, 44]. However, given that fingerprint-based research in the cultural heritage community has not been explored to its full potential, we believe that it can further expand and use some materials and methods investigated in other related fields. In particular, we would like to highlight the following future case studies:

- *3-D-based imaging of ancient fingerprints in cultural heritage*: The 3-D surface imaging could explore the full potential of capturing 3-D ancient impressions; similarly, 3-D volumetric imaging (e.g., CT, magnetic resonance imaging) could investigate the 3-D fingerprints in full depth, with the added advantage to capture also those traces hidden to the external investigation. In the cultural heritage literature, there is already evidence of the transition to 3-D scanning systems (e.g., photogrammetry, laser scanning, structured light) used during various *in situ* excavations [66, 73], obtaining simultaneously a reduction of excavation time without loss of information. The standard patterns (i.e., ridge breadth and ridge density) used to discriminate the sex/age of ancient fingerprints are simple measurements taken from 2-D images, inherently narrowing down the information richness. By using 3-D touchless devices, the analysis could be translated to the 3-D space and enriched by the pool of additional biometric patterns known to be distinctive as the 2-D counterpart. Moreover, the possibility to handle the 3-D model of partial fingerprints of an object could open new investigation lines, like a virtual fingerprint restoration given multiple and matching fragmentary fingerprint pieces.
- *Fingerprint-based artist identification from fired clay sculptures in museum collections*: Fingerprint-based artist identification may represent a revolutionary research avenue for museums with large collections of fired clay sculptures. For example, the Rijksmuseum holds collections of fired clay objects, crafted some centuries ago that survived unchanged to the present day and show fingerprints imprinted in the clay surface. Examples of these collections are the Rijksmuseum's terracotta putti (Figure 8). Based on stylistic grounds, the models are attributed to the Belgian sculptor Jan Baptist Xavery (1697–1742). During the previous restoration of two broken figures, some fingerprints left by the maker were observed at the internal joint between the arm and the shoulders (Figure 8(e)). A recent collaboration between a conservator and a data scientist using CT scanners and computer vision tools [11] has resulted in new research to answer some relevant questions on the authenticity of such objects and their provenance. Conservators from the Rijksmuseum and researchers at the Centrum Wiskunde & Informatica, the CWI, in Amsterdam, have joined their expertise to investigate such partial fingerprints, especially those hidden even to the most experienced observer and only detectable by using a CT scanner, as used in the FleX-ray Laboratory (CWI). We aim to explore the fingerprints of the terracotta works at the FleX-ray Laboratory to compare them with existing pictures and possibly discover some new ones, hidden in the terracotta folds. Furthermore, it

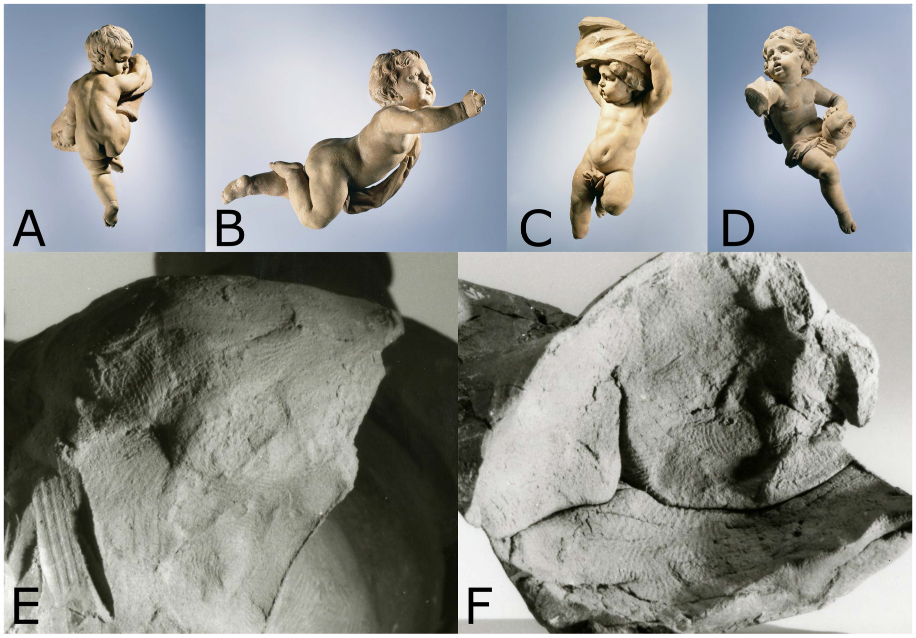

Fig. 8. Four sketches of putti, attributed to Jan Baptist Xavery, terracotta, c. 1725–c. 1750. Parts (a) through (d) correspond to BK-NM-9350, 9351, 9352, and 9353, respectively (Rijksmuseum, Amsterdam, The Netherlands). (e) Fingerprints photographed during restoration on the shoulder of putto BK-NM-9353. (f) Fingerprints photographed during restoration at the internal joint by the shoulder of putto BK-NM-9353.

would allow a comparison with possible fingerprints present on other terracotta works signed and dated by J. B. Xavery and strengthen the attribution of the putti to the artist.

- *Development and maintenance of a digital library of 3-D scanned ancient fingerprints*: The establishment of a 3-D-based archive of ancient fingerprints would allow the original impression information to be preserved with high accuracy, and pose the basis for ancient fingerprint acquisition, digitization, and analysis. Moreover, the development and sustainable maintenance of a digital library for the collection of 3-D scanned ceramic/fired clay sculptures with fingerprints from different museums and private collections could represent a preliminary effort to join forces toward a local, national, and eventually global platform of 3-D fingerprints serving the cultural heritage community. The current health crisis generated by the Covid-19 pandemic sheds light on the necessity and urgency to create such a shared platform for present and future generations of researchers and public. In the Netherlands, PAN (Portable Antiquities of the Netherlands [61]) is the first and only digital open online collection for identifying and categorizing metal objects, designed for and used by professionals for research and detector amateurs. Similar efforts for digital repositories are also witnessed in the dendrochronology world to ensure the long-term preservation and sharing of data [14].

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