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Reconsideration of Bertillonage in the age of digitalisation: Digital anthropometric patterns as a promising method for establishing identity

Marie L. Heuschkel [*], Dirk Labudde

Faculty of Applied Computer Science and Life Sciences, University of Applied Sciences Mittweida, Mittweida, Germany

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ABSTRACT

The idea of using measurements of the human body for identity matching is deeply associated with Bertillonage, a historic biometric system that was briefly applied until it was superseded by fingerprinting in the early 20th century. The apparent failure then commonly causes doubt with regard to the suitability of a set of measurements as a biometric identifier in the present.

Hence, the aim of this paper is to explore the potentials of using an anthropometric pattern, comprising of a set of body measurements, for identity matching. For this purpose, it will begin with a thorough examination of Bertillon's system and move on to conduct a comprehensive inquiry of the current possibilities of using digital anthropometric patterns in image or video-based evidence.

1. Review of existing research

1.1. Introduction to Bertillon's "signaletic system"

Towards the end of the 19th century, „[distinguishing] one individual from another in every case with unerring certainty" [1, p. VII] was still regarded as an „impossibility" [1, p. VII] although the value for any successful investigation and prevention of crimes had already been acknowledged [2].

It was then in 1883 [3] that Bertillon first developed an instrument to serve this purpose, a signaletic system by which he referred to „a new form of applied science which has for its object [the signalment,] a description of any human being in a manner so complete, certain and characteristic that [they] can by no possibility ever permanently be confused with any other." [1, p. VII].

Bertillon apparently saw some similarity between signal transmission and identity matching for he borrowed terms from the former and put it into the context of the latter while retaining some of their original meaning [1]. He called the system signalment, „the description of whom it is desired to identify" [1, p. 11] that may involve „every reception (corresponding to detection) and delivery (corresponding to representation) of human individuality." [1, p. 11] Drawing this kind of comparison is a very clear signal itself that Bertillon was convinced that where proving identity was concerned, it came down to two decisive factors. He defined matching as a „method of elimination taking as its basis the characteristic elements of [human] individuality" [1, p. 12], which constitute the first factor. Presenting it as an establish truth that „nature never repeats herself. Select no matter what part of the human body, examine and compare it carefully in different subjects, and the more minute your examination is, the more numerous the dissimilarities will appear: exterior variations, interior variations in the bony structure, the muscles, the tracing of veins, physiological variations in the gait, the expressions of the face, the action and secretion of the organs, etc … " [1, p. 12]. As a consequence, he argued, „the solution of the problem of judicial identification consists less in the search for new characteristic elements than in the discovery of a method of classification" [1, p. 13].

Even more, Bertillon sought to establish „the application of scientific principles" [1, p. 6] into the practice of establishing identity that so far „[had] been left entirely to instinct, that is, to routine" [1, p. 6].

The science he chose was anthropology, which he saw as a discipline that is „in its definition nothing else than the natural history" [1, p. 6]. Hence, *anthropometrical signalment* as an „application and amplification of anthropology" [1, p. 10] made up a critical part of the threefold *signaletic system*. According to Bertillon the anthropometrical signalment would meet both requirements to the fullest extent: besides offering sufficient „variability …." [1, p. 14] it would be „admirably adapted to classification; this is its aim, its principal purpose, and the reason for its superiority." [1, p. 14].

Yet, while being used for a while, it did not last and by the early 20th century was rendered obsolete by the establishment of fingerprinting [2,

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[*] Corresponding author.
E-mail address: marie.heuschkel@hsmw.de (M.L. Heuschkel).

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3].

In view of all the exuberant statements made by Bertillon, this outcome seems inexplicable.

The aim of this paper is to examine the concept and historical application of anthropometrical signalment as part of the signaletic system (also known today as „Bertillonage“) and to explore the hypothesis that anthropometric measurements are suitable as a biometric identifier in general, and specifically when applied to digital traces such as image and video material. In the course of this investigation, it will also address the question of which specific measurements are best suited for this purpose.

1.2. *Forensic identity matching in a nutshell*

Forensic identity matching involves the comparison of evidence recovered from a crime scene with evidence obtained from a suspected source to determine whether they are similar enough to stem from the same source [4]. The emphasis is put on *similarity* since no two exemplars from the same source will ever be exactly identical due to differences in the circumstances of their acquisition [1,5]. While congruence indeed indicates manipulation, measuring the degree of similarity accounts for intra-individual variability [1,5].

The decision resolving the question regarding provenance and causal relationship is therefore a matter of similarity. Thus, matching can be considered as the continuous process of individualisation [6].

Owing to the strength of the discriminating trait, individuals are progressively excluded from the pool of potential suspects. Individualisation is at its maximum when only one individual remains, resulting in a match and the concurrent establishment of identity [6]. The greater the discriminating power of the trait, the larger the number of potential suspects can be in the pool and a successful result still be attained in the form of exclusion up to matching. Traits that can establish the unique identify a person must be capable of matching without being limited to the size of the pool (i.e., 1: n matching) [7]. They adhere to certain criteria that define their value as a biometric identifier: Universality, permanence or persistence (describing the stability of a trait over time), distinctiveness (as a measure of or uniqueness) and moreover includes the possibility to capture and measure it with the technology available [8–11].

1.3. *The combination of anthropometric measurements as a biometric identifier*

Bertillon also partially took these criteria into account when he chose the 11 head and body measurements of height, length and width (Fig. 1) [1] that made up the anthropometrical signalment as a biometric identifier.

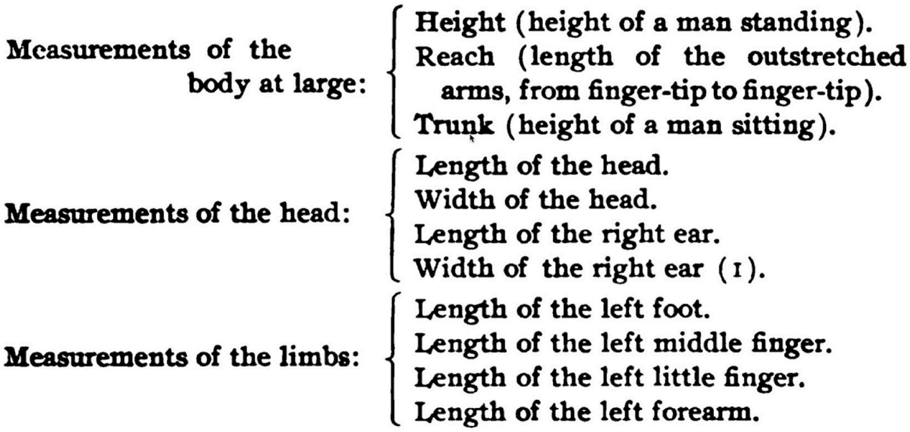
His decision rested upon three facts, for which he cited as evidence his „experience of … ten years [of working with anthropometrical signalment] that has shown to be indisputable: the almost absolute immutability of the human frame between after 20th year of age and old age, the extreme diversity of dimension which the human skeleton presents hen compared in different subjects [and] the facility and comparative precision with which certain dimensions of the skeleton may be measured.“ [1, p. 14–15]. These assumptions reflect the current definition of biometric characteristics.

Anthropometric measurements representing human body dimensions are present in all human beings and as such **universal** [12] with the only limitation being in the number of features e.g., brought about by the loss of a limb. Once an individual is fully grown between the ages of 18 and 21, linear body dimensions that equal bone lengths can be indeed considered permanent until the onset of old age that is associated with a decrease of stature. Nevertheless, stature is also affected by daily fluctuations of between 1,5 and 3 cm, according to the literature, which must be considered accordingly in any comparison, at least methodologically [13–15].

When it comes to **distinctiveness**, later research has accumulated an abundance of empirical evidence supporting Bertillon’s claim of anthropometric measurements displaying substantial individual variation [13,16,17].

Within a single population, individuals of the same height can have widely differing proportions and all kinds of proportions can be found across people of all heights whether they are tall, medium or short [18–20]. According to the empirical results of [21], approximately half of the individuals in a population, regardless of whether they are tall, medium, or short, are proportionally built in the same way. Moreover, it was shown that t there is no such thing as an *average man* since a person that is average in one measurement, then is likely to be beyond the range in many or even most other measurements [21]. Instead, the average should be seen as a theoretical standard from which every human being deviates in some way making them all unequal [12] and hence providing further argument for the uniqueness of humans if not in a single but in a combination of measurements.

A 2016 study [22], the authors investigated the use of body measurements, including circumferences, for uniquely identifying individuals. They analysed data from 3982 U S. Army personnel taken from the 1988 ANSUR anthropometric survey [23], employing a methodology that incrementally adds traits until each individual in the sample is uniquely identified. The likelihood of two individuals having the same measurements for a set of traits is determined through a specific calculation that takes into account the non-correlated elements of the traits and their measurement ranges in millimetres. The study concluded that a combination of eight body measurements reduced the probability of identical matches to 10^{-20}. Compared to their prior work



Measurements of the body at large:
Height (height of a man standing).
Reach (length of the outstretched arms, from finger-tip to finger-tip).
Trunk (height of a man sitting).

Measurements of the head:
Length of the head.
Width of the head.
Length of the right ear.
Width of the right ear (1).

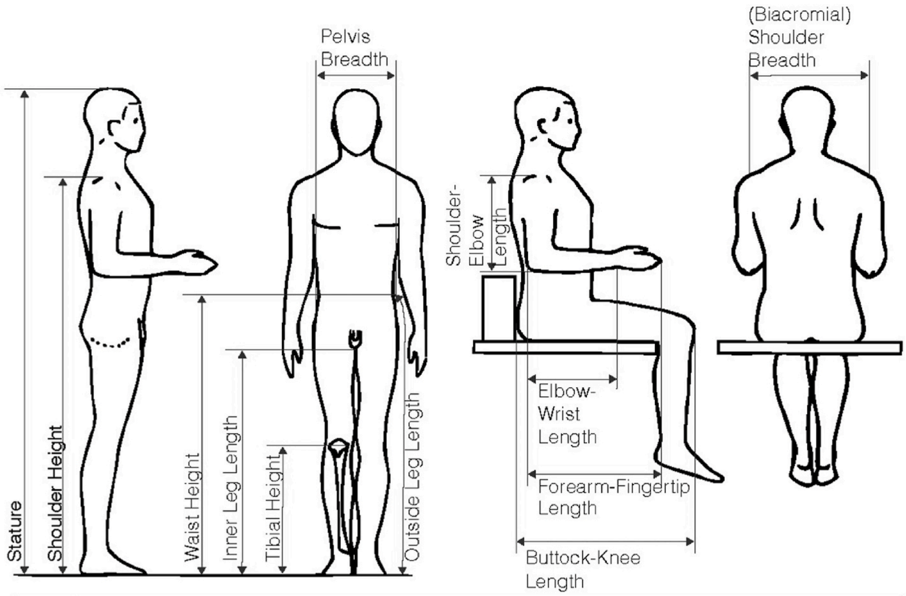
Measurements of the limbs:
Length of the left foot.
Length of the left middle finger.
Length of the left little finger.
Length of the left forearm.

Fig. 1. Overview of the eleven Measurements included in Bertillon’s signaletic system, original excerpt taken from Ref. [1].

on facial measurements [24], they found body measurements to be more effective for identification. A 2019 critique [25], initially focused on the facial measurements [24] but equally relevant here [22], raises questions about the study's scientific foundation. It points out the lack of a mathematical model, scrutinizes the assumptions used in calculating match probabilities—such as uniform distribution, trait independence or their unsupported way of handling interdependencies respectively, and omission of measurement errors—and questions the generalizability of the data set. The critique also underscores practical limitations in forensic contexts, including challenges in matching surveillance footage and inaccuracies in 3D reconstruction.

A recent study [26] compared the measurement sets of 340 individuals taken from a nationwide survey of more than 13.0000 conducted in Germany at the end of the 2000s [27]. The sets consisted of 11 anthropometric measurements [28,29] describing various body dimensions (Fig. 2) that apart from stature differ from the measurement set of the anthropometric signalment. With all these taken into account, there were no two individuals with exact same set of measurements within the data set. The study further backs up the overall exemplary evidence by estimating the probability of obtaining matching measurement sets based on the Euclidean distance involving all 11 measurements as a function of measurement dissimilarity and following a frequentist approach based on kernel density estimations to be in the order of from 10^{-15} to 10^{-8} [26]. In a subsequent study, analytically describable distribution models could be employed for probability estimation, yielding updated probabilities in the range of 10^{-30} to 10^{-21} [30]. These probabilities would depend on both the number and the choice of measurement distances, as demonstrated in the follow-up study [31]. It is important to note that the classification as a match depends on the quality of the data. That includes the resolution of the measurements which in turn relies on the accuracy of the measurement device [26]. With an error of less than 1 mm in the study, values would be classified as a match even if the numerical differences between the values were beyond the level of resolution [27,32]. With further regard to **measurability**, Bertillon's anthropometric signalment required the use of anthropometric instruments that are still in use today and allow one to one-tenth of a millimetre precision [1,33]. However, the measurement process is complex and elaborate and vulnerable to error as there are numerous possible interfering factors [13].

Taking anthropometric measurements requires measurement training and experience so as to be able to observe the measurement instructions including the identification of measurement landmarks and the correct manner of attaching the instruments to the body, for instance. Posture of the subject plays a significant role as well (Fig. 2). Anthropometric Measurements as hitherto known are defined as measurements of linear horizontal and vertical distances. Acting as representations of actual body lengths they only indirectly measure them by overlaying or coinciding with them through specific positioning. This



Feature description	Measurement std.	Resolution (cm)
Stature (body height)	ISO 7250 Nr. 4.1.02	0.1000
Shoulder height (standing)	ISO 7250 Nr. 4.1.04	0.0500
Tibial height	ISO 7250 Nr. 4.1.08	0.1000
Shoulder-elbow length	ISO 7250 Nr. 4.2.06	0.0025
Elbow-wrist length	ISO 7250 Nr. 4.2.07	0.0500
Shoulder (biacromical) breadth	ISO 7250 Nr. 4.2.08	0.1000
Forearm-fingertip length	ISO 7250 Nr. 4.4.05	0.1000
Buttock-knee length	ISO 7250 Nr. 4.4.07	0.0500
Pelvis breadth	RAMSIS 1.1	0.0100
Waist Height	ISO 8559 Nr. 2.2.3	0.1000
Outside Leg Length	ISO 8559 Nr. 2.2.25	0.0500
Inside Leg Length	ISO 8559 Nr. 2.2.27	0.1000

Fig. 2. Set of anthropometric measurements studied [26] in terms of the probability for obtaining a match. The measurements were compliant with ISO 7250 [28,34] and ISO 8559 [29]. The posture of the subject plays an important role in measurement acquisition. Modified figure based on [17,34–36].

may further compromise the measurement of body dimensions extending over several joints, e.g. stature or the length of the whole arm. In sum, there is whole array of aspects that need to be addressed and regulated to ensure accurate and reliable results [13].

In consideration of the current state of knowledge, the assessment of the distinctiveness of body dimensions and proportions turns out to be positive suggesting their suitability as a biometric identifier.

1.4. Limitations of the "signaletic system" that led to its failure

In Bertillon's time identity matching based on the anthropometric signalment alone was not possible for the sole reason that body proportions did not leave any trace at the crime scene. Although photos were also part of the Bertillonage, they could only be interpreted with the help of throughout description provided in the form of two further signalments that together with the anthropometrical signalment made up the signaletic system. Despite Bertillon's correct assertion that methodology largely determines an identification system's success, his signaletic system failed due to methodological limitations.

Bertillon heavily based the matching process on classification assigning measurement values to only a handful of categories per measurement. Qualitative classification weakens the strength of body proportions as a biometric identifier by relying on subjective interpretation, lacking clarity and nuanced distinction of differences, and limiting statistical analysis. Hence, despite meticulously detailed instructions, the signalment remained difficult to implement and the information collected hard to retrieve.

Bertillon insisted that the anthropometric system was final and rejected „every modification , every further change, however slight" [1, p. 19], as they could „only result in augmenting the amount of the possible and inevitable error … „ and „ … [weaken] or [nullify] the signaletic value of an ((anthropometrical)) description [1, p. 16–19]. This inflexibility meant standardization but led to instability.

Bertillon primarily used his authority to support his claims of the „[infallibility]" [1, p. 10] of the signaletic system instead of providing concrete scientific evidence and evaluation to affirm its validity. Furthermore, Bertillon's lack of clarity and explanation hindered the in-depth understanding required for the complex system's implementation, leading to the signaletic system being perceived as too abstract and complicated by others.

It is worth noting that Bertillon lacked formal scientific training or experience and that the signaletic system was developed and tested only within law enforcement environments, without empirical validation or scientific scrutiny.

1.5. 150 Years after Bertillon: the evolution of body measurements and anthropometric identification in the digital age and contemporary research

Given the distinctiveness of human body dimensions and proportions concomitant with anthropometric measurements, the notion of an anthropometric pattern to serve as a biometric identifier can be employed on digital evidence such as images and videos.

Surveillance footage is becoming increasingly abundant in the 21st century with crimes often being captured on camera. That leads to a significant change in the circumstances since the perpetrator's body proportions are now potentially left as digital evidence at the crime scene. This is particularly valuable because perpetrators often try to conceal their faces to avoid recognition [37].

Despite this, the clearance rates in Germany for crimes with and without surveillance footage available do not differ substantially [38, 39]. Furthermore, the clearance rate for crimes in general has been consistently increasing for the past three decades, whereas the clearance rate for crimes with camera surveillance has been stagnating [40]. This demonstrates the ongoing lack of a biometric system to exploit the increasingly ubiquitous image and video material for the use in forensic identity matching [41].

Because of the missing depth information, 2D material such as images is prone to optical and perspective distortion which may severely limit the possibilities of accurately measuring dimensions of subjects or objects depicted such as body proportions [42]. Methods of image and video analysis as those applied within digital forensics [43] as well as methods and principles of 3D-digitisation can effectively address these issues, e.g. by adjusting camera parameters retroactively or reconstructing depth information [44,45].

To further explore existing solutions on anthropometric identification, a literature review was conducted, focusing on keywords such as anthropometric features, biometrics, forensics, identification, video, and surveillance. While not every specific topic, such as height estimation in videos, is individually covered, the search resulted in 92 references that together create a cohesive intersection of relevant themes.

In forensic science, images serve dual roles: they document for illustration and communication while also acting as visual traces for evidence. This dual role extends Locard's Principle, as capturing an image involves a photon transfer from the subject to the camera's recording media, influenced by conditions like lighting, settings, and human intervention. These images are not mere digital reproductions but complex constructs that transform fragments of reality into a unique "photographic reality" requiring critical evidential assessment. The use of images as evidence faces two main challenges: unpredictable creation conditions and rapid technological advancements leading to a plethora of tools often misused by non-specialists. The effectiveness of existing guidelines to mitigate these challenges largely hinges on the operator's skills and experience [46].

Retrieving information from images is a complex, speculative process, essentially reconstructing context through a myriad of factors like physics laws, logic, and additional comparative evidence. This complexity necessitates a formalized investigative framework to minimise distortions. The evidential value of these visual traces is assessed through a hierarchy of explanatory propositions and hypothetico-deductive reasoning, influenced by the potential source population and characteristic frequency. The entire forensic process chain, from image acquisition to storage, impacts their admissibility and integrity as evidence. Increasing the evidential accuracy and reliability can be time-consuming and often infeasible, requiring validation experiments and secure data custody [46]. Hence, a true digital twin is always contextual [47].

1.6. 2D metrology

The term "2D metrology" is employed to refer to existing research focused on measuring from 2D material, such as images or video frames. Its use for person identification has gained significant relevance, especially in the context of rising terrorist attacks and crimes captured on surveillance systems [48]. This practice has been utilized in court cases, as evidenced by Refs. [49,50].

2D metrology for body measurements relies on 2D sources, requiring at least minimal contextual or reference information for accurate analysis. These methods are often developed for immediate application in forensic casework [51], aiming to adapt to a wide range of practical scenarios, from optimal to challenging conditions [52]. Interestingly, the development and exploration of these methods tend to be localized, manifesting in time-limited clusters within the scientific literature.

3D reconstruction from 2D images relies on depth information, achievable through multiple views, reference data, feature points, and camera parameters—the latter being critical for high-accuracy measurements. All methods use calibration, either also addressing distortion in the process or emphasizing that distortion in frames must be negligible, and for that purpose, they require some real-world data [53,54].

Camera calibration involves determining a camera's intrinsic and extrinsic parameters. The intrinsic parameters, such as focal length and optical centre, are internal to the camera. In contrast, the extrinsic parameters relate to the camera's position and orientation in space [55].

Calibration is typically performed using known patterns or objects captured in multiple images from various angles. Algorithms then compute these parameters, which can be either manually identified by an operator or automatically detected by software [56]. Once calibrated, these parameters become crucial for achieving accurate measurements, 3D modeling, and camera-matching techniques [57,58].

All methods feature varying degrees of operator involvement, which is considerable in all cases. The operator's primary role involves the selection of points, either for calibration or for measurement [59,60].

1.6.1. Methods involving 3D subject or Scene Modeling

The work [61] at the National Laboratory of Forensic Science in Sweden primarily focuses on height estimation through 3D modeling based on single-camera frames. Calibration is manually conducted using a digitized ruler, which is recorded by the same surveillance system in various positions covering the area where the subject has been. This ruler serves as a reference for both intrinsic and extrinsic camera parameters, as well as for scaling the subject's measurements. For the measurement process, tracking points are placed at the top of the subject's head and at a point on the floor between their heels. These points are then tracked through the sequence, and the length is calculated based on these tracked points. A unique feature of the Swedish approach is the proposed use of 3D wireframe models, parameterized to represent the subject's anthropometrics. These models are generated using both reverse projection and tracking techniques. The process of 3D motion estimation from a single-camera sequence involves capturing the subject's movement in real-time and converting 2D frames into a 3D representation. The MPEG-4 image compression standard is mentioned as offering one type of these 3D models.Tracking is proposed to be automated. The primary focus remains on height measurement, but the parameterization of other anthropometric features is also proposed, although not yet implemented [61,62].

Studies at the Netherlands Forensic Science Institute utilize 3D Scene Modeling for height estimation generated by means of photogrammetry using multiple calibrated images from a single camera. Specialized software such as 3DMax [63] corrects lens distortion and calibrates intrinsic and extrinsic camera parameters. Reference markers in the scene facilitate calibration, scaling, and alignment within the 3D model. 2D or 3D elements like human body models or cylinders are superimposed onto the image of the perpetrator for precise measurements. The operator manually positions markers on these scaled models to accurately measure height [53,57,60,64–66].

In [58], a specialized 3D modeling technique is implemented. Points at the crime scene are captured using a total station, serving as the basis for constructing a 3D model in Autodesk's 3ds Max. This model is aligned with the actual crime scene images via camera matching in 3ds Max. Camera-matching, involves aligning a 3D model with a 2D image by adjusting the virtual camera's parameters to match the real camera that captured the image, thereby enabling accurate superimposition and measurement. Calibrated images are used to improve accuracy, and distortion correction is applied. For height measurement, a measuring device or probe is positioned at the crime scene.The operator plays an active role in point capturing with the total station, as well as in camera matching and superimposition, making the method semi-automated.

In the case of [52,67], the primary methods for body measurement in forensic video analysis involve the use of a FARO Laserscanner and the software PhotoModeler [68]. These tools facilitate the superimposition and alignment of 3D models onto 2D images captured from single or multiple cameras. Camera matching is particularly emphasized, aligning different camera angles to create a cohesive 3D representation. The images used are generally calibrated, and reference objects within the scene are employed for scaling. The operator manually places markers on key anthropometric points on the 3D models, such as the top of the head and base of the feet. The software then automates the scaling and calculation of measurements like height and arm length. Distortion correction is integrated into the software. The process is semi-automated, requiring manual intervention for marker placement and measurement validation.

Similarly, the approach at the University of Copenhagen's institute of forensic medicine primarily apply stereo photogrammetry, using multiple cameras to capture calibrated images from various angles. Calibration is essential and is performed using known dimensions or control points within the scene, addressing both intrinsic and extrinsic camera parameters. Lens distortions are corrected to ensure accurate measurements. Camera matching techniques align the multiple cameras used in the stereo setup, and scaling is conducted based on reference information. The 3D models of the scene or subject are generated and superimposed onto the captured images facilitated by PhotoModeler. Epipolar lines are utilized to assist in the 3D reconstruction by constraining the search for matching points between the stereo images. Measurements focus on anthropometric features, including height, and are conducted in a semi-automatic manner: the operator sets initial conditions and markers, while the calculations are automated [49,50,69,70].

Akin to Copenhagen, [71] proposes a stereo-photogrammetric system and utilizing PhotoModeler for reconstruction. This approach is unique in that it takes into account a comprehensive set of measurements, while the other works are limited to measuring a person's height.

1.6.2. Methods based on projective geometry

One method [59,72,73] is rooted in projective geometry, a branch of mathematics that deals with the properties and relationships between geometric figures that are projected onto an image plane. It uses this principle to measure heights from a single image. Specifically, the method identifies vanishing points and lines in the image, representing the locations where parallel lines appear to converge when projected onto the image plane. These serve as the minimal geometric information needed for calibrating the scene. This approach doesn't require explicit information about the camera's internal parameters like focal length or orientation. Instead, a known reference height in the scene is used in conjunction with these vanishing points and lines to compute the height of other objects or individuals. To align the 2D image coordinates with the 3D world coordinates, the method employs a 2x2 homography matrix. Homography is a transformation that maps points in one image plane to corresponding points in another image plane, and it's crucial for achieving accurate 2D-3D alignment. If the image has radial distortion, a preprocessing step is applied to correct this distortion. The operator is responsible for manually identifying the vanishing points and lines in the image, which are essential for scene calibration. Additionally, the operator selects a known reference height within the scene to aid in the height computation of other objects or individuals. Height measurement based on projective geometry is also applied at the Netherlands Forensic Science Institute [53,74].

The Measure Tool, initially introduced by Ref. [75] in 1995 and further developed by Ref. [76], is a software designed for single-camera setups. It employs calibrated images and utilizes projective geometry to compute the perspective matrix, which includes both intrinsic and extrinsic camera parameters. The software does offer both manual and automatic scaling options based on known dimensions or reference objects. The tool supports the superimposition of evidence layers for enhanced analysis. Measurements in the Measure Tool are conducted in a semi-automatic mode, where the operator initiates the measurement points. It can measure various features, such as height and distance. Notably, the method does not rely on the existence of a vanishing point; instead, it uses 3D points and lines in the image for calibration and measurements, making the often hard-to-detect vanishing points unnecessary.

The accuracy and reliability of 2D metrology are influenced by a range of factors, including resolution [72], perspective [57] and distance to camera [53,59]. Errors can arise from inaccurate calibration processes or intermittent changes in camera parameters, incorrect intrinsic and extrinsic camera parameters, and lens distortions [77]. Human error and operator-related issues [65] can also be introduced through manual point selection, and software algorithms may have inherent limitations. Inaccurate or missing reference information [53], synchronization issues between multiple cameras [50], and environmental factors and such as lightning [71] or occlusion can further compromise accuracy [69,73]. Furthermore, the posture and movement of the subject to be measured [72] as well as their clothing can easily introduce inaccuracies in the measurements [69]. Additionally, errors can propagate through the system, affecting measurements and 3D model alignment. These cumulative errors impact the overall integrity of modelling reconstruction and measurement process [59].

Next to measurement techniques, studies commonly focus on error analysis to model various sources of error, resulting in either random or systematic measurement uncertainties [57]. These analyses utilize a spectrum of statistical modelling approaches, from frequentist methods [65] to Bayesian Hierarchical models [66]. Evaluation experiments mostly rely on small sample sizes [53,78].

Some of the methods attain their best accuracy for height measurements within a range of ±1 to 1.5 cm under optimal conditions [58,70,72]. However, this level of accuracy significantly deteriorates under less favourable conditions [66,69].The significance of the biometric value of height for person identification is often debated, but generally accepted as useful for distinguishing individuals with notable height differences [48]. In forensics, height measurements can complement more definitive methods like DNA or fingerprint analysis, especially in cases where such material is unavailable [61]. These measurements are primarily used to exclude suspects whose anthropometric data significantly differ from the perpetrator's [52]. In Ref. [49] evaluation follows a subjective, "European Union-approved conclusion scale" [49, p. 2] developed by the European Network of Forensic Science Institutes [79], which ranges from "Identification" to "Exclusion". While several authors mention existing guidelines for handling and processing digital data [46,61], only [59] proposes procedural guidelines specifically tailored for height measurement from images within a forensic context. Using single-view metrology as an illustrative example, he emphasizes the uncertainties that characterize the final measurement. Such uncertainties, contributing to error propagation, must be managed through a standardized approach that encompasses all steps of the process chain for both error assessment and quality assurance. These arguments give the notion that a standardized procedure can serve as an extension to the method itself, embedding it within a practical framework designed to account for, understand, and reduce uncertainty. Steps such as preliminary assessment, data collection, and pre-processing become integral parts of the method.

Further work in this field that complements the topics on 2D metrology discussed can be found in Refs. [56,80–87].

1.7. Anthropometric pattern extraction and matching

To mitigate operator bias in image video metrology, another body of work has set the focus on automatisation of feature processing and comparison, intersecting with the field of re-identification [88–94].

Re-identification aims to consistently recognize the same individual across different images or video frames, even when there are significant time gaps or viewpoint changes. Unlike biometric identification, which assigns a unique identity based on stable and unique biometric features like fingerprints or iris patterns, re-identification is more concerned with consistency in recognizing the same individual without necessarily knowing their unique identity. Re-identification often shares methodologies with object tracking, which focuses on maintaining an accurate representation of an object's state and position, and biometric recognition, which aims for exact identity verification. The techniques employed in re-identification are increasingly diverse, ranging from appearance-based methods that focus on visual cues like colour and texture, to machine learning algorithms that may incorporate elements of soft biometrics. Soft biometrics are characteristics that don't fulfil the criteria of a biometric identifier, such as uniqueness or permanence, but can still be useful for identification. The field is evolving and these various approaches often overlap and are integrated into comprehensive systems, making the distinctions increasingly nuanced. [95]

The focus of these studies lies on the design, recognition, extraction, and matching performance of distinctive features [96,97]. Rather than a single measurement, they deal with digital anthropometric pattern [98], i.e. a set of digital features representing lengths and widths defined by keypoints commonly referred to as a skeleton in the literature [99]. Methodologies employ computer vision, e.g. Refs. [77,82–84], machine learning, e.g. Ref. [100], and deep learning, e.g. Refs. [98,101,102], often using Microsoft Kinect [37,97,100,103–117]for depth sensing or drawing from 3D models, Euclidean distances based on anthropometric survey data [118,119](e.g. CAESAR [23] [96,120–122])) or 2D as well as 3D pose estimation frameworks [123–134]. Notably, only few publications propose anthropometric patterns as biometric features for identification on their own [98,105,116,131]. Instead they are usually combined with other descriptors like body shape [97] or gait [101,135,136].

Evaluation metrics show fluctuating accuracy, e.g. a precision rate ranging from 0.61 to 0.91 in an anthropometric pattern based on 2D the pose estimation OpenPose [131].

Nevertheless, these approaches still face similar challenges like 2D metrology including occlusion, pose variance, and background clutter.

Further work in this field that complements the topics discussed can be found in [137].

1.8. Conclusions from the literature

The inherent challenge that serves as the source of all error stems from two key factors: having accurate reference information and the ability to recognize or detect the correct information in the image (points and lines) [59]. This recognition can be done either visually, as in 2D metrology, or through computational methods like computer vision, machine learning, or deep learning. Any factor that influences either of these aspects can introduce potential errors. This is why projective geometry, which interprets straight lines in images, is generally less robust than 3D modeling approaches [53]. The latter can leverage more real-world information for more consistent and stable estimations, particularly when camera orientation varies or when lighting conditions, occlusions, and noise can affect the accuracy of geometric transformations [72].

Examining research from the mid-1990s to the present reveals a rather insular landscape, with minimal cross-disciplinary exchange. For instance, image or video metrology rarely intersects with 2D pattern extraction and matching [9,77,83,85]. Furthermore, progress seems to plateau, as evidenced by similar methodological descriptions in publications 15 years apart [49,50], suggesting either stagnation or a belief that the method has reached its pinnacle.

This research often takes on a case-study character, particularly in forensic settings where balancing practicality and scientific rigor is challenging. Practical conditions are frequently suboptimal; for example, reference lengths may be unavailable, and the variables introduced by surveillance cameras—such as unknown focal points, lens distortion, and low resolution—complicate height measurements. These issues are exacerbated by the subject's own characteristics, like pose and attire, and by cost-saving measures like using single camera setups, which hinder accurate 3D reconstruction by photogrammetry.

The focus on existing forensic conditions often leads to methodological compromises aimed at gathering as much evidence as possible. However, this single-strategy approach may conflict with long-term applicability. Unpredictable conditions can easily render a method ineffective, and the complexity of each system makes ad-hoc adjustments impractical, increasing uncertainty.

Experiment and evaluation designs often lack a comprehensive methodological framework, leading to ambiguous definitions and a lack of clear underlying principles for evaluation approaches. For instance, since sample size is usually small, Bayesian statistics would be preferable choice to describe the unknown errors with probability distributions [138]. Yet only one study selected this approach [66].

Since the methods draw from multiple subject areas, it is compounded by insufficient expertise from other fields, giving the impression of a more pragmatic than scientifically rooted approach. Validation efforts are often limited to small contexts and sample sizes, undermining their generalizability.

Lastly, while leveraging existing technologies such as Computed Generated Imagery (CGI) is beneficial, it's crucial to recognize that these technologies were developed for different purposes and may not be directly transferable. Overall, the field would benefit from a more integrated, transparent, and scientifically rigorous approach.

To instigate meaningful change, it's essential to establish the missing links in the chain of forensic science. with bridging Bertillon's anthropometric concepts to their digital counterparts, thereby transferring analog methods to digital applications in forensic science.

Another vital link is established by raising awareness among law enforcement agencies about the potential of digital anthropometric pattern matching, as seen in interdisciplinary collaborations and joint projects between law enforcement authorities and forensic experts in Germany.

Adopting a dual strategy that embeds digital pattern matching in both scientific research and practical application establishes a vital link for mutual exchange. This fosters a conducive environment for continuous validation and robust modelling, allowing for rigorous experimental designs that can adapt to real-world complexities. The practical challenges to notions of 'uniqueness' and 'individualisation' [139] given the empirical nature of anthropometric measurements, this approach also necessitates solid mathematical models and analytical methods [140,141]. This also gives way to the notion inspired by Ref. [59] for a framework that is both scientifically and practically grounded, making it an intrinsic part of the method. This dual strategy aligns with the principles of the Daubert Standard—empirical technique, peer-reviewed publication, forensic medicine acceptance, and tested reliability—making it suitable for admissibility as court evidence [48,69].

Interdisciplinary efforts serve as another crucial link, facilitating the transfer of scientific knowledge across various disciplines. This enables the integration of distinct clusters such as re-identification, automation, and image or video metrology, which have traditionally operated in isolation. It also bridges the divide between technology users and experts, creating a more cohesive ecosystem. Technological considerations also form part of this link. While technologies developed for CGI may offer some utility, they are not inherently suited for forensic applications. Therefore, a balanced approach is needed, one that judiciously combines existing technologies with new innovations tailored for forensic needs. Parallel to this, there is an imperative to upgrade equipment, particularly in terms of resolution and installation, to meet the demands of forensic science.

2. Conception of digital anthropometric pattern matching for biometric person identification

Building upon existing research, this paper introduces its own method and corresponding framework for digital anthropometric pattern matching.

2.1. Digital anthropometric pattern matching as a biometric system

Digital Anthropometric Pattern Matching is a biometric system based on those digital anthropometric patterns as the biometric identifier offering elements and processes for capturing, extracting, quantitatively comparing as well as evaluating the pattern as the carrier of biometric information.

The biometric identifier is a set of body lengths, widths and heights forming an anthropometric pattern specific to an individual. Unlike other pattern comparison evidence [4], the anthropometric pattern itself is not left as a mere impression on the crime scene but is captured as a tangible representation on 2D material, potentially enabling the extraction of precise and accurate biometric data for use in forensic investigations.

Hence, to allow for comparisons between the probe and a reference pattern, it is crucial to address the divergences caused by the absence of depth information, the resolution of the video or image and the parameters of the camera. This is accomplished through the conversion into 3D resulting in a digital reconstruction of the recorded scene.

To achieve the depiction of natural proportions, artists use hypothetical constructs by dividing the body into segments and assuming a part of the body (, e.g. the spine) as a basic measure, called the modulus, which is contained in each body segment in n-fold length. In this way, they create a proportional framework [142].

Informed by this idea and aiming to create an anthropologically useful pattern of the body, the measurement points are selected in a way where the resulting measurements, which are depicted according to their true length form an anthropometric pattern that in turn best represents the underlying musculoskeletal system (Fig. 3) [142,143].

A digital 3D model of a potential suspect (, i.e. the source) is generated by means of photogrammetry or 3D scanning. **Capturing** the biometric data, this model is the true depiction of the real-life subject from which the anthropometric pattern is then **extracted** and transferred into an abstracted digital 3D-Model, a digital skeleton called *rig*. It only contains the data of the biometric identifier and serves as the *reference pattern*, also called *reference rig*.

Furthermore, a digital 3D model of the crime scene and its surrounding environment, including the surveillance cameras, is created. Moreover, the configuration of the virtual cameras of the model is adjusted to comply with their real-life equivalents. This enables the projection of the surveillance footage onto the model, allowing for the virtual simulation of the course of events.

The projection of the footage enables the superimposition with the virtual 3D scene allowing to reconstruct the real dimensions of the perpetrator and subsequently extract the *probing pattern* or *probing rig* from the 2D information.

In the matching process, the *Probing rig* is then **quantitatively compared** to the pool of *reference rigs* by means of superimposition measuring the score of similarity in space or by means of their Euclidean distances measuring the similarity based on the measurement values [144].

In terms of the interpretation of the results, the **criteria for evaluation** constitute of the classification as a match or non-match based on statistically determined threshold values. These take into account the quality and possible sources of error, such as the false match rate (Type I error) and false non-match rate (Type II error) [145,146].

2.2. Embedding digital anthropometric pattern matching in forensic science

Digital anthropometric pattern matching can be of great use, especially in the field of Forensic Sciences and within the context of prosecution as well crime prevention. For this reason, it is imperative to ensure that the system and its application are thoroughly and sustainably rooted in science. That kind of scientific integrity can be accomplished by exposing it to scientific scrutiny and testing for its evaluation and validation as well as by surrounding it with a vast body of scientific research [147].

This scientific framework, which must hold for all biometric identifiers and biometric systems, comprises several key aspects that need to be applied to digital anthropometric matching.

The first and foremost aspect involves the rigorous statistical validation and description of the system. This includes the relevant statistical evaluation and verification of the biometric system's processes in general, as well as the metric person matching and classification of

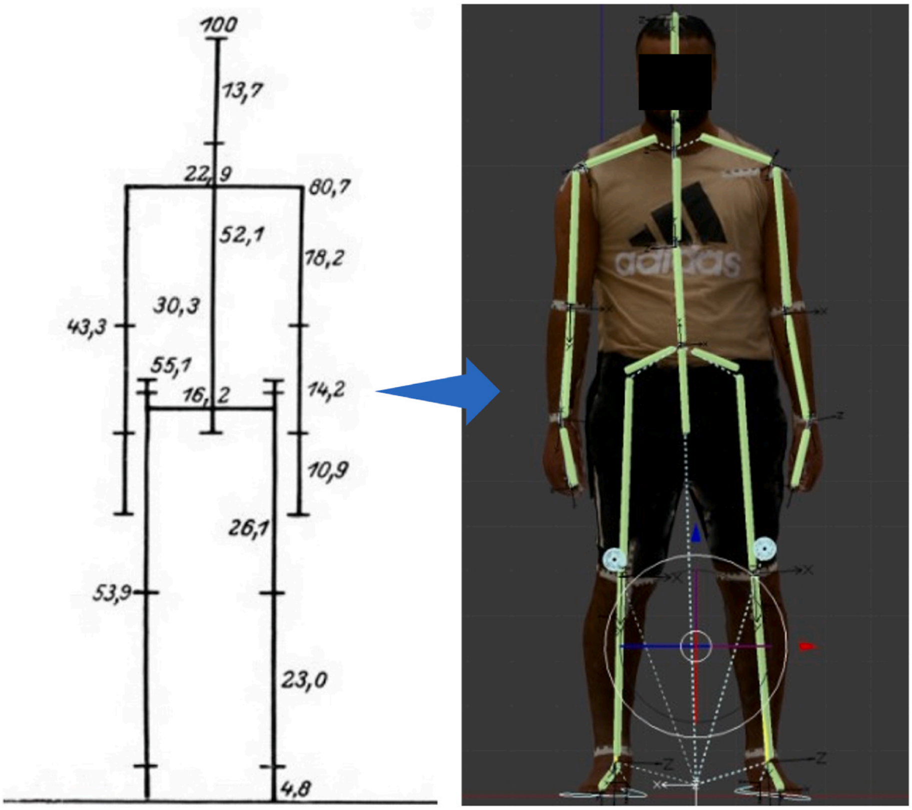


Fig. 3. Left: Proportional figure by Martin [143]. In contrast to Bertillon's set of measurement, the selected proportions represent the underlying musculoskeletal system. Numbers show the percentage of individual measurements in relation to height (set at 100 for each individual). Right: A digital 3D model of a potential suspect and the suspect's derived rig representing the digital anthropometric pattern.

matches in particular. What is more, to further explore deviations during matching, approaches such as Bayesian modelling ought to be taken into consideration, which go beyond point estimations and allow for the incorporation of multiple model probabilities, the meaningful averaging of these probabilities, and the appropriate quantification of uncertainties in conclusions [30,138]. Furthermore, it is important to describe deviations or similarities as analytically as possible [31].

To minimise the possibility of a false conviction due to misclassification, it is also necessary to statistically determine the occurrence probability of a match as well as the evaluation of the individual comparison between two rigs taking into account deviation caused by measurement and quality conditions as well intervals of the intra-class variation (deviations between different rigs of the same person) and inter-class variation (deviations between different rigs of different persons) [145,146,148].

Furthermore, to account for possible influencing factors including the quality of the image or video material (number of pixels exposure, sharpness, format and camera perspective), visibility of the digital anthropometric pattern, as well as common and unusual postures and clothing of the individual to be analysed, it is critical to evaluate them in experiments that are that are designed, executed, and analysed in accordance with the Scientific Method [149,150].

A third aspect encompasses scientific principles [151] that ultimately assure the credibility, reliability, and integrity of a biometric system. They include the accuracy and reliability to ensure and clearly demonstrate the degree to which results are accurate, reproducible (based on the same data and research), replicable (using different data but the same approach), robust (across different studies with the same data), and generalisable (across different studies with different data) [152,153].

Transparency and traceability of a biometric system are essential for maintaining data authenticity, while clarity ensures the entire process is understandable to all those involved or otherwise concerned. As seen with Bertillonage, explainability leading to a profound understanding by those who execute and use it is essential for the realization and acceptance of the biometric system of digital anthropometric pattern matching [151,154].

The basic principle of digital anthropometric pattern matching was first used by Dirk Labudde in the context of the persecution of the theft of the Big Maple Leaf Gold Coin weighing a 100 kg and featuring a purity of 99,999 % from the Bode Museum in Berlin in 2017, where the perpetrators were captured by surveillance cameras at a train commuter train station on their way to the museum. Aware of the camera and its location, the perpetrators intentionally hid their faces. There were five suspects determined during the investigation [155,156].

The image identification expert report ought to clarify whether the individuals captured on the surveillance footage matched these five suspects with the aim of establishing or excluding their possible involvement in the crime. Rigs representing the anthropometric pattern were derived from photogrammetric 3D models of 5 suspects. Concurrently, a 3D model of the site, including the surveillance camera, was generated. The virtual camera was configured in such a way that it mirrored its physical equivalent. In the next step, the scene from the surveillance footage, the 3D model of the site, and the 3D model and rig of the suspect are superimposed, leading to the reconstruction of the 3D scene depicted in 2D on the surveillance footage. Once the suspect's 3D models and rigs correctly overlay the perpetrator's 2D depiction, the 3D model is faded out and the rig compared with the perpetrator. The reconstructed 3D scene and the superimposed rig allowed for the rig's as well as the perpetrator's measurement, including their standing height and shoulder height. This way the rig of each suspect was compared with each perpetrator and either matched or mismatched in a simple binary procedure resulting in the assignment of four suspects to the respective perpetrator depicted on the footage and the exclusion of one suspect

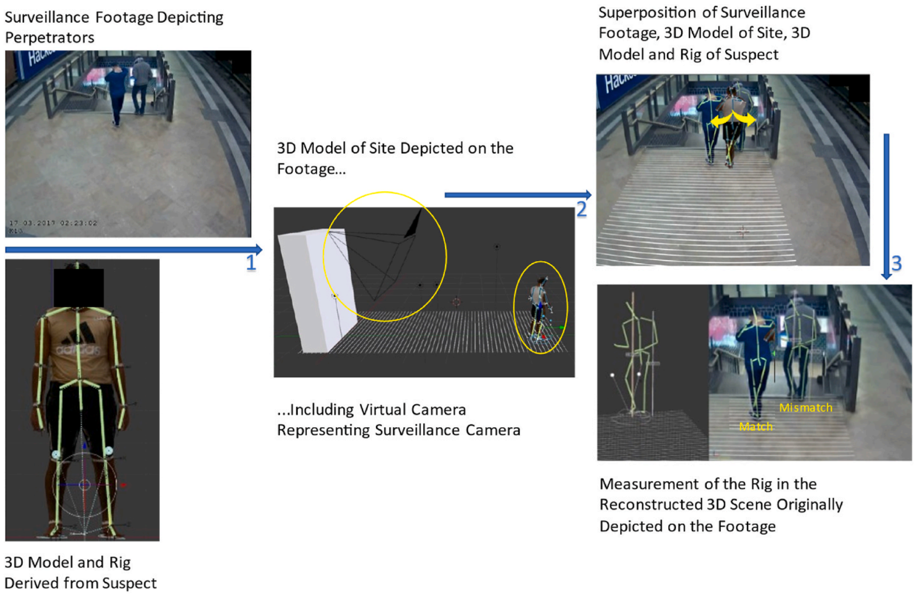


Fig. 4. Procedure of the first application of the basic principles of anthropometric pattern matching in the case of the Big Maple Leaf Theft from Berlin's Bode Museum in 2017. 1, Left Below And Centre: A photogrammetric 3D model of the suspect is first generated. It serves the basis for the derivation of the rig that represents the anthropometric pattern. 1, Above and Centre: A 3D model of the site, the commuter train station, including its surveillance cameras is generated. The virtual camera is configured to work identically to its physical counterpart. 2: the scene from the surveillance footage, the 3D model of the site, and the 3D model and rig of the suspect are superimposed, leading to the reconstruction of the 3D scene depicted in 2D on the surveillance footage. Once the suspect's 3D models and rigs correctly overlay the perpetrator's 2D depiction, the 3D model is faded out and each rig compared with each perpetrator in the scene either using a binary procedure and resulting in either a match or a mismatch. The suspect in this figure matched the perpetrator on the left on the footage.

(Fig. 4).

Additionally, several items of clothing secured during the investigation, which were also assigned to the perpetrators on the footage, as well as similarities in posture and gait between suspects and perpetrators were also considered in the assessment. Photographs of the suspects from police ID procedures and comparative material from the surveillance cameras were further consulted for purposes of verification and safeguarding.

The judge acknowledged the expert report and admitted it during the main trial. The court, however, chose not to follow the conclusions of the expert report citing "methodological deficiencies" such as a lack of standardisation and validation. The methodological approach is comparable to the one applied at Copenhagen, whose evidence was admitted and found significant in a court case as recently as 2019. Lynnerup explicitly mentions one case where the "court admitted our evidence and found it significant." [50], p. 6 Hence, the success of evidence assessment may hinge not only on scientific methodology but also on its effective transfer into practical application. Nevertheless, since 2017 the methodology has undergone further development and first scientific results have been obtained [26,30,31,44,45,144].

3. Conclusion and outlook

There is a constant race between new forensic methods and the perpetrators' attempts to evade them while committing a crime: While the ever-increasing amount of image and video material available ought to facilitate law enforcement and crime prevention, criminals can significantly reduce the usefulness of such digital material easily by covering or disguising their faces.

Digital anthropometric pattern matching counteracts this in several ways as it can utilize the increasingly ubiquitous digital 2D material. Not only is the anthropometric pattern digital preserved on the image or video, but the comparison is made amidst the dynamics of the crime since the method reconstructs the original moment that was captured by camera. The transfer into the 3rd dimension allows for an unaltered comparison of digital traces. Thus, there is a wide range of potential fields of application for digital anthropometric pattern matching, encompassing multiple types of offences.

After initial research and a first practical application have demonstrated the general functionality and suitability of digital anthropometric pattern matching, the goal is now to expand the concept of this image-based biometric system and implement it. This comprises continued development and relevant statistical embedding, validation and application of the method on a larger sample. Additionally, the limitations of the method need to be more clearly defined.

Once a solid foundation has been laid this way for the establishment of a new, technologically advanced biometric method in the context of law enforcement, it will then require the increasing integration of possibilities for automatisation as well as thorough legal-ethical safeguarding, so that digital anthropometric pattern matching can be transformed into a standardised method. This would constitute an evolution from the usage within individual expert reports to an application that is suitable for mass use, including the ability of 1:n comparisons from a database, in the context of prosecution, if it is desired by the rule of law.

A biometric system based on these principles leads to gaining and maintaining trust. Only through acceptance based on these standards can the biometric system of digital anthropometric pattern matching truly be established.

The goal should be to achieve a state-of-the-art comparable to that set by DNA matching and demonstrate that the biometric system is capable of „consistently, and with a high degree of certainty [establishing] a connection between evidence and a particular individual source." [147].

3.1. Key insights and future directions

There are two pivotal aspects to consider with regard to the usage of forensic methods in generating evidence that in turn is presented in court. The first "concerns the question of whether – and to what extent- there is science in any given 'forensic science' discipline" [157, p. 87].

In the reality of forensic science, actual methods and techniques tend to be developed primarily to gain evidential insight regarding a particular case and its peculiarities [157]. This approach not only makes them compromised, but also neglects conducting the necessary continuous research into their scientific basis, soundness, and limitations, which is crucial for validating their reliability and accuracy. As evidence produced by forensic methods used in legal proceedings can significantly impact the verdict and the fate of the accused, ensuring accuracy, reliability and thus justice is paramount. On the one hand, this means the courts must proceed with caution to minimise the risk of confirming methods with unverified reliability [158]. Meanwhile, delaying the use of methods until research is completed can be counterproductive [158], as it may result in the loss of valuable evidence and is not in line with the actual progression and creation of research opportunities. It is important to acknowledge both a method's or technique's capabilities and the serious ramifications in case of its misapplication. The main challenge, therefore, is to bridge the gap between applying scientific forensics and conducting research in laboratory conditions gradually accumulating the required body of research. This encompasses understanding error rates, characterizing, and determining the quality requirements of sample materials, both from crime scenes and reference samples for comparison.

Hence, it cannot be understated that the methodologies must be anchored in two fundamental principles: transparency and scientific rigor, leading to a clear assessment of their validity.

Transparency, among others, involves moving away from statements that suggest absolute certainty, such as "to the exclusion of all others" [158, p. 905], such as exclusivity, and instead working transparently with, for instance, relative plausibility [159].

As scientific models, which form the statistical basis for statements about probability or plausibility, are general and representative in nature, they cannot be solely relied upon to resolve specific and complex individual judicial cases [157]. The forensic scientific expert must demonstrate the degree of similarity between two samples measured and compared using existing technologies, and the deviation from all other possible samples using scientific model-based extrapolation. This involves scientific conclusions that do not address the question of guilt [157].

A process operated by humans inevitably carries a potential for error, e.g. regarding the authenticity or the origin of a sample, that extends throughout the process of criminal investigation and thus cannot be confined to a single method's error model. Simultaneously, these error potentials may diminish a scientific statistical model's robustness [157].

Scientific conclusions are not judicial decisions that consider the particularities, context and complexities of individual case realities [157]. Therefore, the second pivotal aspect concerns the correct allocation by the trier of fact in legal proceedings, of which scientific forensic results and expert testimonies form a part [158,157]. It entails logically assigning questions and statements as well as avoiding logical fallacies such as circular reasoning (the person was correctly matched because they were found guilty at trial) and the prosecutor's fallacy (equating the rarity of evidence with the probability of a suspect's guilt) [157].

The forensic expert is required to present evidence, and, in their role as an assistant to the court, provide the court with all necessary information in a transparent and understandable manner, enabling the legal decision-making authority to appraise the evidence [157]. This also involves a legal classification of forensic methodology within the framework of evidentiary rules, including standardized definitions of terms like similarity and individuality.

The imperative for a contextual and case-specific evaluation of evidence holds especially true in the case of digital anthropometric pattern matching yet should also apply to all forensic methods and approaches in general, extending to accepted ones such as dactyloscopy, which nevertheless still lacks methodological and empirical statistical evaluation, as well as DNA analysis [158,157].

In summary, forensic science must navigate the delicate balance between providing scientifically sound evidence and understanding its role within the broader judicial system. While forensic methods provide invaluable tools for evidence analysis, their application must be approached with caution, humility, and a deep understanding of their scientific and legal implications. This approach ensures the protection of individual rights and the integrity of the judicial process.

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Marie L. Heuschkel: Conceptualization, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Dirk Labudde:** Conceptualization, Methodology, Supervision, Visualization, Writing – review & editing, Data curation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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